



SURGERY PLANNING AND BED ALLOCATION WITH APPLICATION TO A
MILITARY HOSPITAL'S ORTHOPAEDIC DEPARTMENT

Gustavo Carneiro

Dissertação de Mestrado apresentada ao Programa de Pós-graduação em Engenharia de Produção, COPPE, da Universidade Federal do Rio de Janeiro, como parte dos requisitos necessários à obtenção do título de Mestre em Engenharia de Produção.

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*A alguém cujo valor é digno
desta dedicatória.*

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Agradeço primeiramente a Deus por me dar forças na busca do pão de cada dia.

À minha esposa Bianca e aos meus filhos, Gabriel e Guilherme, obrigado por todo o apoio. Agradeço a Papai do Céu diariamente por ter vocês em minha vida.

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Com base nas necessidades de um hospital militar, este trabalho apresenta um problema integrado de programação de cirurgias e planejamento de leitos pós-cirúrgicos para um ambiente hospitalar. O cenário dá origem a um problema geral de modelagem em cuidados de saúde com uma série de inovações literárias. O modelo utilizado inclui múltiplas rotas de recuperação pós-cirúrgica, considerando possíveis estadias na Unidade de Terapia Intensiva (UTI) ou Semi-Intensiva (UTSI), e permite ao decisor atribuir um plano de alocação de leitos que considera o tempo máximo de permanência nestas unidades pós-operatórias. A abordagem foi concebida para garantir um fluxo contínuo de pacientes, evitando o cancelamento de cirurgias por restrições insuficientes a jusante, e permite um planejamento tático que considera o equilíbrio a longo prazo entre demanda e oferta de cirurgias em todas as especialidades.

Para validar o modelo e investigar a sensibilidade em relação aos parâmetros e à disponibilidade de recursos, utilizamos uma série de experimentos com base no funcionamento real do hospital em questão. Os resultados mostram que a modelagem pode também ser utilizada em outros hospitais, e fornece apoio à decisão na prestação de serviços cirúrgicos, tendo em conta toda a trajetória do paciente, bem como os recursos a montante e a jusante.

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Based on the needs of a military hospital, this work presents an integrated surgery scheduling and post-surgical bed planning problem for a standard hospital setting. The setting gives rise to a general healthcare modelling problem with a number of innovations with respect to the literature. The model includes multiple post-surgical recovery trajectories involving possible stays at the Intensive Care Unit (ICU) or Semi-Intensive (SICU) and allows the decision maker to assign a bed allocation plan that considers the maximum length of stays in these postoperative units. The approach is designed to ensure a seamless patient flow, avoiding surgery cancellations due to insufficient downstream resources, and enables tactical planning that considers the long-term balance between demand and surgery provision across all specialties.

To validate the model and investigate the sensitivity with respect to model parameters and the availability of resources, we use a series of experiments that were based on the actual operation of the hospital partner. The results shows the performance that the model can tackle a general hospital setting and provide decision support for surgical provision while taking into account the whole patient trajectory, as well as both upstream and downstream resources.

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Chapter 1

Introduction

The need to properly plan and manage resource intensive hospital services such as surgery provision has been accentuated by the combination of ageing populations and limited budgets across the globe (e.g., CYLUS *et al.*, 2022). Indeed, the literature on surgery scheduling has steadily increased over the last decade and it includes a number of important literature reviews on the topic (DEMEULEMEESTER *et al.*, 2013; SAMUDRA *et al.*, 2016; WANG *et al.*, 2021). However, since this is a complex problem, some specific issues still remain under-explored or unaddressed. Integrated tactical planning covering both upstream (e.g., operating theatres) and downstream resources (e.g., post-surgical beds at different recovery units) is an example of the former (WANG *et al.*, 2021; HARRIS and CLAUDIO, 2022); as well as the gap between theory and practice mentioned by WANG *et al.* (2021). In contrast, tactical planning considering the integration of multiple post surgical units across distinct hospital recovery pathways is an example of the latter.

Bridging theory and practice, the present study is motivated by a partnership with a military hospital in Rio de Janeiro, Brazil. The hospital partner required decision support with their tactical elective surgery scheduling planning for the orthopaedic centre. However, albeit their surgical pathways follow a standard setting, there was no approach in the literature to tackle the associated surgery scheduling and bed assignment planning in its entirety; hence a new modelling approach was required. It is this new modelling approach that we introduce in this study. The next section briefly discusses the hospital setting and the modelling challenges.

1.1 The studied setting

The centre for orthopaedic surgery at the hospital partner is a leading regional centre of its kind, with a large demand for elective surgeries and a waiting queue which currently holds about 750 surgical patients. Due to the size of the waiting queue, one of the concerns of the tactical planning to be proposed is that it generates a schedule with some excess capacity relatively balanced across the medical specialities, to make sure that the waiting queue for each speciality will decrease in the long-term.

The operating theatres are open from Monday to Friday, and are compatible with each of the seven orthopaedic specialities served at the hospital's orthopaedic centre, namely: foot, hand, shoulder, knee, spine, hip, and paediatric. Figure 1.1 illustrates the entire flow from hospital referral to discharge, with the bottom part representing the flow at the surgical centre that is modelled in this study. Observe that, after surgery, the patient is transferred to the postoperative recovery centre, where they stay until they are ready for hospital discharge. The last two blocks in Figure 1.1 are detailed in Figure 1.2.

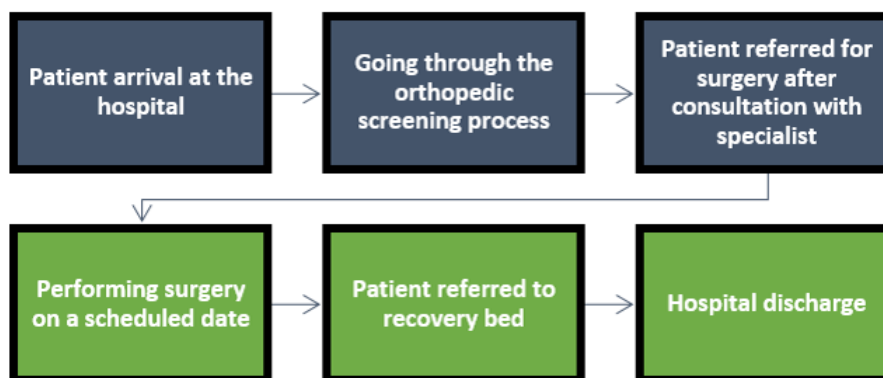


Figure 1.1: Patient flow from hospital arrival to hospital discharge.

Notice that Figure 1.2 details the downstream processes, i.e., the post-surgical care provided by the orthopaedic centre. It is a general, albeit fairly standard setting that includes three different recovery units: the Intensive Care Unit (ICU), the Semi-Intensive Care Unit (SICU) and the Ward. To the best of our knowledge, this setting remains unaddressed in its entirety in the literature concerning tactical surgery scheduling. It generates a set of patient pathways that can include visits to

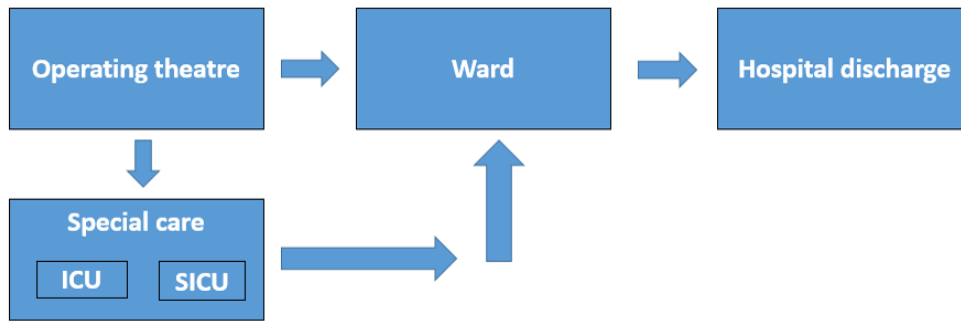


Figure 1.2: Flow between operating theatre and recovery units.

either ICU or SICU prior to the final recovery at the Ward and subsequent discharge from hospital. While patients that do not require special care are immediately referred to the Ward, those that do will visit either the ICU or the SICU depending on their individual requirements. SICU receives patients that require special care but no permanent monitoring, whilst patients that require both will be referred to the ICU.

To address the problem introduced above, we propose a general model with a number distinguishing characteristics and novel contributions to the literature. Firstly, it tackles an integrated surgery scheduling and bed planning problem that covers the whole patient trajectory, from surgery to discharge, whilst covering multiple recovery pathways that may include intensive or semi-intensive care prior to the final recovery in the Ward and posterior hospital discharge. Secondly, the model combines open block surgery scheduling that allows different specialities to share operating theatres, with bed capacity allocation at all three recovery units (ICU, SICU and Ward) to balance input and output patient flows; and it does so by considering the worst-case-scenario for the lengths of stay at ICU and SICU, thus introducing some robustness to the downstream planning. Thirdly, the weekly schedule is integrated with the downstream capacity planning to ensure that the surgery plans remain viable whilst demand and capacity constraints make sure that the capacity exceeds the demand for all surgical specialities, thereby integrating tactical planning with the hospital's long-term objective of decreasing the waiting queues.

The rest of the work is structured as follows. The next chapter features a brief literature review that contrasts our approach to the related literature. Chapter 3 introduces the proposed mathematical model and explains its connection to the

studied problem. To validate the proposed approach and to discuss its implications, Chapter 4 introduces a set of experiments based on the operation of the hospital partner. The experiments also analyse the variation of the resulting weekly surgery schedules and bed assignment plans with changes in the operating theatre capacity and in the model parameters. Finally, Chapter 5 concludes the work.

Chapter 2

Literature Review

The management of surgeries at the hospital level comprises two different classes of interrelated problems: surgery planning and surgery scheduling (ZHU *et al.*, 2019; AKBARZADEH *et al.*, 2019). Whilst planning typically involves determining a set of surgeries to be performed within a time horizon, surgery scheduling can be seen as determining the exact schedule of patients that will have surgery at an specified date (AKBARZADEH *et al.*, 2019). These are widely studied problems that have been reviewed by several authors in recent years (e.g., SAMUDRA *et al.*, 2016; WANG *et al.*, 2021; HARRIS and CLAUDIO, 2022; ZHU *et al.*, 2019; GÜR and EREN, 2018). Like the majority of works in the area, this work focuses on the planning of elective surgeries.

Surgery planning problems can be divided into three different decision levels: strategic, tactical and operational (e.g., SAMUDRA *et al.*, 2016; WANG *et al.*, 2021; HARRIS and CLAUDIO, 2022; ZHU *et al.*, 2019). Issues at the strategic level have a long-term time horizon and aim to improve the use of available hospital resources and their distribution across medical teams (e.g., CHOI and WILHELM, 2014; RIISE *et al.*, 2016; FÜGENER *et al.*, 2017). The tactical level looks at a medium-term horizon (e.g., ABEDINI *et al.*, 2016; PENN *et al.*, 2017; BRITT *et al.*, 2021) and aims to bridge the gap between the strategic and the operational level. The latter, in turn, has a short-term time horizon such as the scheduling of surgeries for a single day (e.g., ZHANG *et al.*, 2021; YOUNESPOUR *et al.*, 2019; BAM *et al.*, 2017). This study addresses a tactical-level surgery planning problem.

At the tactical level, a surgery planning problem is often referred to as a Master

Surgery Scheduling Problem (MSSP) and produces a cyclical schedule for assigning surgeries to different medical teams or specialities over a given period, which often amounts to one week (HARRIS and CLAUDIO, 2022; ZHU *et al.*, 2019). Many studies, however, consider only short-term performance measures aimed at reducing financial costs, such as those related to the use of resources or professional labour (e.g., ABEDINI *et al.*, 2016; DELLAERT and JEUNET, 2017; ROSHANAIEI *et al.*, 2017; TAYYAB *et al.*, 2023), ignoring long-term issues such as reducing waiting queues across surgical specialities. These issues, nonetheless, are vital to linking the daily operation with the hospital’s long-term goals (RACHUBA *et al.*, 2022; SIQUEIRA *et al.*, 2018). Therefore, our approach will link tactical planning with long-term goals by ensuring that the prescribed capacity for surgeries exceeds the demand across each individual speciality - a sufficient condition for the long-term stability of the waiting queues.

Another important concept relates to the hospital’s strategic policy for assigning medical teams to operating theatres. There are two main classes of policies for sharing operating theatres, namely *open block* and *closed block* (e.g., WANG *et al.*, 2021; HARRIS and CLAUDIO, 2022; ZHU *et al.*, 2019). Closed block policies assign each operating theatre (OT) for exclusive use by a single medical team for a prescribed length of time - often a day (e.g., KOPPKA *et al.*, 2018; GUIDO and CONFORTI, 2017; ROSHANAIEI *et al.*, 2020; ZHU *et al.*, 2020). In contrast, open block policies allow OTs to be shared between different medical teams or surgical specialities (e.g., ROSHANAIEI *et al.*, 2017; HASHEMI DOULABI *et al.*, 2016; TAYYAB and SAIF, 2022). Whilst open block policies involve additional management issues such as co-ordinating different medical teams or surgical specialities, they expand the number of possible configurations of surgery sessions and can therefore promote a better usage of the OT capacity (e.g., BRITT *et al.*, 2021; SIQUEIRA *et al.*, 2018). In our study, we considered a single medical team available for each speciality and chose the open block approach to allow greater flexibility in the assignment of surgeries and promote a better usage of the OTs, as open block policies are welcome by our hospital partner.

In terms of the types of models used in the problems, the majority of the literature use deterministic models (e.g., DELLAERT and JEUNET, 2017; TAYYAB *et al.*, 2023; ZHU *et al.*, 2020). Some researchers use stochastic modelling to account

for uncertainties in the time required to perform each surgery (e.g., DELLAERT and JEUNET, 2017; MAKBOUL *et al.*, 2022) or in the patient’s recovery time after surgery (e.g., DELLAERT and JEUNET, 2017; CAPPANERA *et al.*, 2014). Mathematical programming is the most used solution method for tactical-level problems (WANG *et al.*, 2021), but some authors also use simulation (KOPPKA *et al.*, 2018; CAPPANERA *et al.*, 2014). To reduce the computational time for finding satisfactory solutions, some authors use heuristics (DELLAERT and JEUNET, 2017; GUIDO and CONFORTI, 2017; ZHU *et al.*, 2020; TAYYAB and SAIF, 2022).

This work introduces a tactical-level integrated surgery planning and bed management problem with a number of important characteristics that differentiate it from the previous literature. Similarly to SIQUEIRA *et al.* (2018), we consider an integrated open block surgery planning problem which also assigns post-surgical beds to surgical specialities, with a view to improving the patient flow by optimising the use of upstream and downstream resources. To promote long-term equilibrium, the approach makes sure that the assigned number of weekly surgeries exceeds the demand over the same period for each surgical speciality. Our study innovates, however, by considering different routes of post-surgical recovery (see Figure 1.2) that include stays at either the Intensive Care Unit (ICU) or the Semi-Intensive Care Unit (SICU). To the best of our knowledge, this is the first surgery planning approach that considers the flow of patients through a SICU - a link between the operating theatre and the ward that provides postoperative care for patients who do not require permanent monitoring, but still require intensive care (EKELOEF *et al.*, 2019).

Considering SICU and ICU into the patient flow model is important not only because it renders the model more realistic, but also due to the high financial cost of these units, whose demand comes mainly from the operating theatres (HEIDER *et al.*, 2020). Furthermore, the lack of postoperative ICU and SICU beds propagates in the system, causing surgery cancellations and potential delays in subsequent surgeries. Whilst some previous studies also considered the ICU in their model (e.g., DELLAERT and JEUNET, 2017; TAYYAB *et al.*, 2023; MAKBOUL *et al.*, 2022; ANJOMSHOA *et al.*, 2018), to the best of our knowledge the proposed model is the first to consider recovery routes that can include either an ICU or a SICU stay, each with a given probability that depends on the surgical speciality. Furthermore, while

previous works considered fixed ICU capacities for each speciality, our model also prescribes the allocation of the available beds at each post-operative unit (SICU, ICU and Ward) to surgical specialities, to promote an optimised flow of patients.

Finally, another important contribution of the approach is that it ensures a balance between input and output at both the ICU and the SICU for each day of the planning horizon, by considering the worst case scenario in terms of length of stay at these units. This confers some robustness to the resulting surgery and bed allocation plans, with a view to improving patient flow and preventing surgery cancellations due to the absence of downstream resources.

Table 2.1: References - Surgery planning.

Approach / Reference		AGNETIS <i>et al.</i> (2014)	CAPPANERA <i>et al.</i> (2014)	VANCROONENBURG <i>et al.</i> (2015)	HASHEMI DOULABI <i>et al.</i> (2016)	ABEDINI <i>et al.</i> (2016)	DELLAERT and JEUNET (2017)	ROSHANAIE <i>et al.</i> (2017)	PENN <i>et al.</i> (2017)	GUIDO and CONFORTI (2017)	ANJOMSHOA <i>et al.</i> (2018)	KOPPKA <i>et al.</i> (2018)	SIQUEIRA <i>et al.</i> (2018)	AKBARZADEH <i>et al.</i> (2019)	MARQUES <i>et al.</i> (2019)	ZHU <i>et al.</i> (2020)	ROSHANAIE <i>et al.</i> (2020)	BRITT <i>et al.</i> (2021)	TAYYAB and SAIF (2022)	MAKBOUL <i>et al.</i> (2022)	TAYYAB <i>et al.</i> (2023)	This work	
Type of problem	Planning	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
	Scheduling	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Decision level	Tactical	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Operational	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Strategy	Closed block	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Open block	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mathematical model	Deterministic	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Stochastic	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Solution method	Simulation	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Mathematical programming	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Heuristic	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Considered resources	OT	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Ward	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	ICU	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	SICU	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Shared resources	OT	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Ward	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	ICU	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	SICU	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Objective (reduce)	Financial costs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Waiting time	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 2.1 summarises the proposed approach according to the main classifications discussed above and compares it to the related literature. Note that some works address planning and scheduling (e.g., TAYYAB *et al.*, 2023; ZHU *et al.*, 2020; AGNETIS *et al.*, 2014; VANCROONENBURG *et al.*, 2015). First, at the tactical level, they create schedules that assign surgeries to operating theatres; then, at the operational level, they assign individual patients to scheduled slots. The next

chapter introduces and discusses the proposed mathematical model in detail.

Chapter 3

Mathematical model

The proposed mathematical model covers the process from entry into the operating theatre to discharge from the hospital. The parameters of the problem are described in Table 3.1, the modelling parameters are in Table 3.2, and the decision variables are in Table 3.3.

Table 3.1: Parameters of the problem.

Parameter	Description
$S = \{1, \dots, N_s\}$	Set of specialities
$T = \{1, \dots, N_r\}$	Set of operating theatres available for surgeries
$D = \{1, \dots, N_d\}$	Set of days available for performing surgeries
Ope_s	Time, in hours, to perform surgery of speciality $s \in S$.
C_T	Time, in hours, for preparing and cleaning of operating theatres
Rec_{ward_s}	Maximum time, in days, that the patient of speciality $s \in S$ stays in the ward after surgery
N_{icu_e}	Time, in days, that the patient of speciality $s \in S$ stays in the ICU after surgery
N_{sicu_s}	Time, in days, that the patient of speciality $s \in S$ stays in the SICU after surgery
H	Total hours available for performing surgeries in each operating theatre
$Int_{s,d}$	Time, in days, since the last probable surgery of the speciality $s \in S$, measured on the day $d \in D$
Dem_s	Weekly demand for surgeries of speciality $s \in S$
P_{icu_s}	Minimum percentage of surgeries of the speciality $s \in S$ requiring patient recovery in the ICU
P_{sicu_s}	Minimum percentage of surgeries of the speciality $s \in S$ requiring patient recovery in the SICU
$Beds_{ward}$	Number of beds available in the ward
$Beds_{icu}$	Number of beds available in the ICU
$Beds_{sicu}$	Number of beds available in the SICU
$U_{t,d}$	1, if the operating theatre $t \in T$ can be used on the day $d \in D$, 0, otherwise
$B_{s,d}$	1, if surgeries of speciality $s \in S$ can be performed on the day $d \in D$, 0, otherwise

Table 3.2: Modeling parameters.

Parameters	Definiton
W	Parameter limiting the number of beds allocated in the recovery units
M_1	Arbitrarily large parameter that limits the number of daily surgeries of each speciality at any operating theatre
M_2	Arbitrarily large parameter that limits the number of daily surgeries of each speciality

Table 3.3: Decision variables.

Variables	Definition
$x_{total_s,t,d}$	Total number of surgeries of speciality $s \in S$ assigned to operating theatre $t \in T$, on day $d \in D$
$x_{icu_s,t,d}$	Number of surgeries of speciality $s \in S$ assigned to operating theatre $t \in T$, on day $d \in D$, which require patient recovery in the ICU
$x_{sicu_s,t,d}$	Number of surgeries of speciality $s \in S$ assigned to operating theatre $t \in T$, on day $d \in D$, which require patient recovery in the SICU
$x_{ward_s,t,d}$	Number of surgeries of speciality $s \in S$ assigned to operating theatre $t \in T$, on day $d \in D$, whose patient recovery occurs directly in the ward
y_{icu_s}	Number of ICU beds allocated to speciality $s \in S$
y_{sicu_s}	Number of SICU beds allocated to speciality $s \in S$
y_{ward_s}	Number of ward beds allocated to speciality $s \in S$
$z_{s,t,d}$	1, if operating theatre $t \in T$ is allocated to speciality $s \in S$ on day $d \in D$, 0, otherwise

Figure 3.1 details the flow of patients from operating theatre to hospital discharge, considering their multiple recovery pathways. Observe that patients of any given speciality can be referred to the ICU or SICU after surgery in case they need SICU or ICU care. Otherwise, they will be directly referred to the Ward. Finally, patients will be discharged from hospital after their recovery at the Ward.

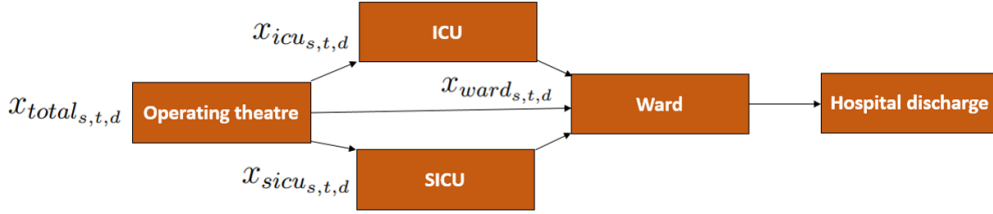


Figure 3.1: Quantities of patients in the flow between the operating theatre and hospital discharge.

Equation (3.1) below introduces the optimisation problem to be solved:

$$\text{Maximise } \sum_{s \in S} \sum_{t \in T} \sum_{d \in D} (Ope_s * x_{total_s,t,d}) - W * \sum_{s \in S} (y_{icu_s} + y_{sicu_s} + y_{ward_s}), \quad (3.1)$$

subject to (3.2) – (3.18).

Observe that the left-hand side of Eq. (3.1) represents the total time effectively assigned to surgeries during the planning horizon, whereas the right hand side is a weighted sum of the number of beds allocated. Therefore, the aim is to maximise the utilisation of the surgical centre, whilst limiting the number of post-surgical beds allocated across the different units. This is intended to help the decision-maker manage possible fluctuations in the availability of downstream resources by

maintaining a reserve of bed capacity to use when needed.

Constraint (3.2) ensures that the number of hours required to perform all surgeries assigned to an operating theatre (OT) on a given day, including cleaning and preparation, never exceeds the hospital limit of H hours (Table 3.1) on days in which the OT is available

$$\sum_{s \in S} (Ope_s + C_T) * x_{total,s,t,d} \leq (U_{t,d} * H) + C_T, \forall t \in T, \forall d \in D. \quad (3.2)$$

The parameter $U_{t,d}$ (Table 3.2) on the right hand side of expression (3.2) ensures that no surgery will be assigned on days when the OT is not available. The last term in the right-hand side of (3.2) represents an extra cleaning and preparation interval, as both the preparation for the first surgery and the cleaning of the last one can be done outside of the working hours.

Constraints (3.3) and (3.4) below concern the allocation of operating theatres to surgical specialities and their corresponding medical teams

$$M_1 * z_{s,t,d} - x_{total,s,t,d} \geq 0, \forall s \in S, \forall t \in T, \forall d \in D; \quad (3.3)$$

$$\sum_{t \in T} z_{s,t,d} \leq 1, \forall s \in S, \forall d \in D. \quad (3.4)$$

Whilst (3.3) ensures that surgeries of speciality s can only be assigned to OT t on day d if theatre t is assigned to speciality s on day D ($z_{s,t,d} = 1$, see Table 3.3), constraint (3.4) guarantees that, if active on day $d \in D$, the medical team responsible for surgeries of speciality $s \in S$ will perform all their surgeries in a single OT. Note that this constraint does not prevent different specialities sharing the same OT. Instead, it is a sufficient condition to prevent any surgical speciality $s \in S$ from being assigned two concomitant surgeries in different OTs (inconsistent assignment). The parameter M_1 (Table 3.2) is an arbitrarily large positive integer ("big M ").

Elective surgical procedures follow a weekly schedule so that surgeries can only be assigned to the speciality s on day d if a medical team of that speciality is available. Thus, constraint (3.5) states that surgeries of speciality $s \in S$ can only be performed on day $d \in D$ if the correspondent medical team is present

$$\sum_{t \in T} x_{total_{s,t,d}} \leq B_{s,d} * M_2, \forall s \in S, \forall d \in D. \quad (3.5)$$

Note that the parameter $B_{s,d}$, (Table 3.1), on the right hand side of the inequality (3.5), prevents surgeries of speciality s from being scheduled on days when the corresponding medical team is absent. The parameter M_2 (Table 3.2) on the right hand side of the inequality is also an arbitrarily large positive integer (“*big M*”), and in this case, it acts as a bound on the total number of surgeries of speciality $s \in S$ assigned on day $d \in D$.

For long-term management of the queues across all specialities, to prevent them from growing uncontrollably, constraint (3.6) establishes that the minimum number of surgeries of the speciality $s \in S$ assigned throughout the week must exceed, in at least one unit, the weekly demand for surgeries of the respective speciality, represented in Table 3.1 by parameter Dem_s :

$$\sum_{t \in T} \sum_{d \in D} x_{total_{s,t,d}} \geq Dem_s + 1, \forall s \in S. \quad (3.6)$$

As a complement to constraint (3.6), and to avoid an excessive number of surgeries, constraint (3.7) states that, for each speciality, the total number of surgeries over the planning horizon cannot exceed a prescribed upper bound, namely the rounded up value equivalent to one and a half times the demand over the same period.

$$\sum_{t \in T} \sum_{d \in D} x_{total_{s,t,d}} \leq 1.5 * Dem_s + 1, \forall s \in S. \quad (3.7)$$

This is intended to result on a relatively balanced schedule across all specialties, to ensure that an eventual spare capacity in the OTs is not fully assigned to a small subset of specialties.

The remaining constraints model the post-surgical patient flow depicted in Figure 3.1, starting with equation (3.8) below:

$$x_{total_{s,t,d}} = x_{icu_{s,t,d}} + x_{sicu_{s,t,d}} + x_{ward_{s,t,d}}, \quad (3.8)$$

$$\forall s \in S, t \in T, d \in D.$$

Eq. (3.8) establishes that the total number of surgeries of speciality $s \in S$ assigned to operating theatre $t \in T$ on day $d \in D$, represented by the variable $x_{total_{s,t,d}}$ (Table 3.3), will be split between surgeries requiring patient recovery in the ICU ($x_{icu_{s,t,d}}$), surgeries requiring recovery in the SICU ($x_{sicu_{s,t,d}}$) and surgeries whose patients can be directly sent to the Ward ($x_{ward_{s,t,d}}$).

It is noteworthy that $x_{icu_{s,t,d}}$ and $x_{sicu_{s,t,d}}$ are auxiliary variables to help us plan the required ICU and SICU bed capacity according to the expected number of surgeries requiring a stay at each of these units. Constraints (3.9)-(3.10) ensure that we plan ICU (SICU) bed capacity for a minimum of P_{icu_s} (P_{sicu_s}) percent of the total number of surgeries of each speciality $s \in S$ on each day $d \in D$ (see Table 3.1):

$$\sum_{t \in T} \left(x_{icu_{s,t,d}} - x_{total_{s,t,d}} * \frac{P_{icu_s}}{100} \right) \geq 0, \forall s \in S, \forall d \in D; \quad (3.9)$$

$$\sum_{t \in T} \left(x_{sicu_{s,t,d}} - x_{total_{s,t,d}} * \frac{P_{sicu_s}}{100} \right) \geq 0, \forall s \in S, \forall d \in D. \quad (3.10)$$

To balance entries and exits in the special care units for each speciality, constraints (3.11) and (3.12) specify that the number of patients of speciality $s \in S$ who are in the ICU and the SICU, respectively, on day $d \in D$ is limited to the total number of beds allocated to that speciality. The left side of each constraint represents the sum of the quantities of patients of speciality $s \in S$ sent to ICU and SICU beds in the last N_{icu_s} and N_{sicu_s} days (Table 3.1), respectively:

$$\sum_{t \in T} \sum_{k=0}^{N_{icu_s}-1} x_{icu_{s,t,d-k}} \leq y_{icu_s}, \forall s \in S, \forall d \in D. \quad (3.11)$$

$$\sum_{t \in T} \sum_{k=0}^{N_{sicu_s}-1} x_{sicu_{s,t,d-k}} \leq y_{sicu_s}, \forall s \in S, \forall d \in D. \quad (3.12)$$

Notice that, by establishing N_{icu_s} (N_{sicu_s}) as the maximum length of stay at the ICU (SICU) for a patient of speciality $s \in S$, we attain some robustness for the bed planning at these units, which will help us guarantee that the weekly plan will not be hindered by the lack of downstream resources.

Constraint (3.13) states that if surgeries of speciality $s \in S$ can be scheduled on

day $d \in D$, then the total number of new patients arriving at the Ward is limited to the number of free beds for that speciality on that day

$$\begin{aligned} \sum_{t \in T} x_{ward_s, t, d} + \sum_{t \in T} \sum_{k=0}^{Int_{s,d}-1} x_{icu_s, t, d-k-N_{icu_s}} + \sum_{t \in T} \sum_{k=0}^{Int_{s,d}-1} x_{sicu_s, t, d-k-N_{sicu_s}} &\leq \quad (3.13) \\ &\leq \frac{y_{ward_s}}{Rec_{ward_s}} * Int_{s,d}, \forall e \in E, \forall d \in D, Int_{s,d} > 0. \end{aligned}$$

Note that the right hand side of the constraint represents the number of patients of speciality s leaving the ward beds in the interval of $Int_{s,d}$ days (i.e., since the last day when surgeries of speciality s were undertaken - see Table 3.1), where $1/Rec_{ward_s}$ is the average number of patients of this speciality discharged daily per recovery bed. This average value is considered in the ward to represent the high outflow of patients in this recovery unit.

The left hand side of (3.13) respectively aggregates the patients who underwent surgery on day d and were transferred directly to the ward, plus those who came from the special care units: those who have recovered in the ICU and SICU for N_{icu_s} and N_{sicu_s} days, respectively, and who arrived at the ward in the last $Int_{s,d}$ days.

In complement, constraint (3.14) guarantees that in case new surgeries of speciality $s \in S$ cannot be performed on day $d \in D$ ($B_{s,d} = 0$ and $Int_{s,d} = 0$), the total number of patients of said speciality arriving at the ward on this day does not exceed the average number of released beds:

$$\sum_{t \in T} x_{icu_s, t, d-N_{icu_s}} + \sum_{t \in T} x_{sicu_s, t, d-N_{sicu_s}} \leq \frac{y_{ward_s}}{Rec_{ward_s}}, \forall s \in S, \forall d \in D. \quad (3.14)$$

Constraint (3.15) states that the number of patients of speciality $s \in S$ arriving at the ward on day $d \in D$ is limited to the number of beds allocated to the speciality in question. Note that this figure is composed of patients who came directly from the operating theatre, added to those from the special care units, who had their recovery period in the N_{icu_s} and N_{sicu_s} days before:

$$\sum_{t \in T} x_{ward_{s,t,d}} + \sum_{t \in T} x_{icu_{s,t,d-N_{icu_s}}} + \sum_{t \in T} x_{sicu_{s,t,d-N_{sicu_s}}} \leq y_{ward_s}, \quad (3.15)$$

$$\forall s \in S, \forall d \in D.$$

Constraints (3.16), (3.17) and (3.18) establish that the totals of beds allocated across all specialities $s \in S$ are restricted to the quantities available in the hospital in each postoperative unit, represented by the parameters $Beds_{icu}$, $Beds_{sicu}$ and $Beds_{ward}$ (Table 3.1):

$$\sum_{s \in S} y_{icu_s} \leq Beds_{icu}. \quad (3.16)$$

$$\sum_{s \in S} y_{sicu_s} \leq Beds_{sicu}. \quad (3.17)$$

$$\sum_{s \in S} y_{ward_s} \leq Beds_{ward}. \quad (3.18)$$

Constraints (3.19) and (3.20) assume that the decision variables that assign surgeries and allocate beds (Table 3.3) belong to the set of non-negative integers:

$$x_{total_{s,t,d}}, x_{icu_{s,t,d}}, x_{sicu_{s,t,d}}, x_{ward_{s,t,d}} \in \mathbb{Z}_+, \forall s \in S, \forall t \in T, \forall d \in D; \quad (3.19)$$

$$y_{icu_s}, y_{sicu_s}, y_{ward_s} \in \mathbb{Z}_+, \forall s \in S. \quad (3.20)$$

Finally, constraint (3.21) states that the decision variable that allocates operating theatres (Table 3.3) is binary, being equal to 1 if OT $t \in T$ is allocated to speciality $s \in S$ on day $d \in D$, or equal to 0 otherwise:

$$z_{s,t,d} \in (0, 1), \forall s \in S, \forall t \in T, \forall d \in D. \quad (3.21)$$

Next, in Chapter 4, we present some numerical experiments that validate our approach and provide some insights into the effects of varying parameters such as the

weekly demand for surgeries, the number of available operating theatres across the week and the penalty for allocating extra beds in the post-surgery units - SICU, ICU and Ward.

Chapter 4

Numerical experiments

We start this chapter by introducing the baseline parameters for our experiments. These were obtained from our military hospital partner and cover their operation from January to December, 2022. These are the model parameters listed in Table 3.1, which will be detailed in the next section.

4.1 General parameters for the experiments

The number of daily working hours H at each OT is equal to 12 hours, whereas the surgery preparation and cleaning time C_T is set to 30 minutes; we should bear in mind that the cleaning up of the last surgery and the preparation of the first one can be performed outside the OT working hours. As previously mentioned, the hospital covers a set S comprised of 7 orthopaedic specialities. As for the operating theatre availability, it varies across the week and the precise number of OTs available at each day will be individually introduced for each of the experiments. Hence the set T of operating theatres will vary across experiments, as well as the weekly availability of individual theatres. Finally, elective surgeries will only be performed from Monday to Friday.

Table 4.1 shows the schedule of the medical team of each speciality during the week, represented in the model by parameter $B_{s,d}$. The table conveys the availability of the medical teams during the week, with $B_{s,d} = 1$ if the medical team for speciality s is available on day d and $B_{s,d} = 0$ otherwise. One can see, for example, that the paediatric surgery team will perform surgeries only on Mondays and Fridays, whereas

hip surgeries can take place on any day from Monday to Friday.

Table 4.1: Weekly schedule of surgeries by specialities (parameter $B_{s,d}$).

Speciality / day	Monday	Tuesday	Wednesday	Thursday	Friday
Hip	1	1	1	1	1
Spine	1	1	1	1	1
knee	1	1	1	1	1
Shoulder	1	1	1	1	1
Hand	0	1	0	1	1
Foot	1	0	1	1	0
Pediatric	1	0	0	0	1

Table 4.2 depicts the model parameter $Int_{s,d}$ for all specialities across the week. Recall that $Int_{s,d}$ measures the interval (in days) since the last day that the medical team for speciality s was available to perform surgeries. For the example, as the medical team for the shoulder speciality is available from Monday to Friday - 4.1, $Int_{s,d} = 1$ from Tuesday to Friday. On Monday, however, the parameter value is equal to 3 days, representing the time elapsed between Friday and Monday.

Table 4.2: Time interval between surgeries of the same speciality (parameter $Int_{s,d}$).

Speciality / day	Monday	Tuesday	Wednesday	Thursday	Friday
Hip	3	1	1	1	1
Spine	3	1	1	1	1
Knee	3	1	1	1	1
Shoulder	3	1	1	1	1
Hand	0	4	0	2	1
Foot	4	0	2	1	0
Pediatric	3	0	0	0	4

The time required to perform surgery in the speciality $s \in S$, represented by the parameter Ope_s , and the postoperative hospitalisation times in the different units, required for patient recovery in the respective speciality, indicated by Rec_{ward_s} , N_{icu_s} and N_{sicu_s} , are illustrated in Table 4.3.

Table 4.3: Surgery and recovery time (Ope_s , Rec_{ward_s} , N_{icu_s} and N_{sicu_s}).

Speciality	Hip	Spine	Knee	Shoulder	Hand	Foot	Pediatric
Surgery time by speciality (hours)	2.8	3	2	2	1.3	1.2	1.5
Length of post-surgical stay in the ward (days)	2.2	2.5	2	2	1	1.1	1
Length of post-surgical ICU stay (days)	7	7	4	4	1	1	1
Length of post-surgical SICU stay (days)	1	1	1	1	1	1	1

Table 4.4 comprises a set of parameters that vary only with respect to the surgical speciality, namely: the weekly demand for surgeries (Dem_s), the minimum

percentage of surgeries that require recovery in the ICU (P_{icu_s}) and the minimum percentage of surgeries that require recovery in the SICU (P_{sicu_s}).

Table 4.4: Demand and percentage in the ICU and SICU (Dem_s , P_{icu_s} and P_{sicu_s}).

Speciality	Hip	Spine	Knee	Shoulder	Hand	Foot	Pediatric
Weekly demand for surgeries	3.6	3.4	8	7.5	5.5	6	3
Minimum percentage of surgeries requiring patient recovery in ICU	50	50	15	15	0	0	0
Minimum percentage of surgeries requiring patient recovery in the SICU	50	50	25	25	0	0	0

Finally, Table 4.5 shows the number of beds available in the ICU ($Beds_{icu}$), in the SICU ($Beds_{sicu}$) and in the Ward ($Beds_{ward}$).

Table 4.5: Beds in the ICU, SICU and Ward ($Beds_{icu}$, $Beds_{sicu}$ and $Beds_{ward}$).

Post-surgical recovery bed	Number of beds available
ICU	16
SICU	8
Ward	100

In the remainder of this section, we will introduce specific sets of experiments and discuss its results and implications.

4.2 Experimental results

The series of experiments to be presented in the next sections were run using the Gurobi Optimizer version 9.1.2 (Gurobi Optimization, LLC, 2022) on a laptop computer with Windows 10 operating system, 2.27 GHz i5 processor and 8 GB RAM. To limit the execution time, we utilised a maximum gap of 2% when searching for solutions using the branch and bound algorithm. The referenced value is expressed by $\text{Gap} = \frac{UB-LB}{LB}$, where UB and LB are equivalent to the values of the upper (dual) bound and lower (primal) bound, respectively.

4.2.1 Analysis of the effects of increasing operating theatre capacity

This subsection proposes the first set of experiments, which is comprised of experiments A1-A5. Starting from the baseline instance (experiment A1), we gradually

increase operating theatre availability and observe the effects of the increase on the resulting optimal weekly surgery schedule and bed allocation plans across the ICU, the SICU and the Ward.

Table 4.6 shows the weekly demand for surgeries for all specialities $s \in S$; we also present the maximum number of weekly surgeries which would be assigned as per constraint (3.7), which limits the weekly number of surgeries to prevent an excessive bias in the weekly allocation. These parameters will remain constant over experiments A1-A5.

Table 4.6: Demand and upper bounds for experiments A1-A5.

Speciality	Demand (Dem_s)	Upper Bound ($1.5 * Dem_s + 1$)
Pediatric	3	5.5
Spine	3,4	6.1
Hip	3,6	6.4
Foot	6	10
Hand	5,5	9.25
Shoulder	7,5	12.25
Knee	8	13

Table 4.7 details the OT availability for experiments A1 to A5; notice that the penalty for each post-surgical bed allocated in the optimal solution is set to $W = 1$ in all experiments - see the objective function (eq. (3.1)). Experiment A1 utilises the minimum number of operating theatres to attain feasibility. For the other experiments, OTs are gradually added along the week; each change of OT capacity with respect to the previous experiment is illustrated in red in Table 4.7.

Table 4.7: Experiments A1 to A5.

Experiment	Parameter W	Number of operating theatres available				
		Monday	Tuesday	Wednesday	Thursday	Friday
A1	1	2	2	2	2	2
A2		3	2	2	2	2
A3		3	2	3	2	2
A4		3	2	3	3	2
A5		3	2	3	3	3

Let us start by analysing the optimal weekly Master Surgery Schedule (MSS) for experiment A1, depicted in Figure 4.1. One can see an intense occupation of the surgical centre across the whole week. One important measure related to the optimal MSS is the *time assigned for surgeries*, that corresponds to the first summation in the objective function - eq. (3.1), and amounts to 96.3 hours distributed across a total of 49 surgeries. Another measure of interest is the *total length of the OT sessions* which adds up the time elapsed from the outset of the first surgery to the

end of the last surgery across all operating theatres. This amounts to 115.8 hours in experiment A1, as it includes the preparation and cleaning operations performed during the working hours. Finally, the *overall occupation rate* of a MSS represents the ratio between the *total length of the OT sessions* and the total time available for surgeries in the whole surgical centre - measured as a percentage. As we have a weekly total of 120 hours available for surgeries (2 OTs, each with 12 daily working hours, open five days a week), the *overall occupation rate* for experiment A is 96.5% - as the *total length of the OT sessions* (115.8 hours) corresponds to 96.5% of 120 hours.

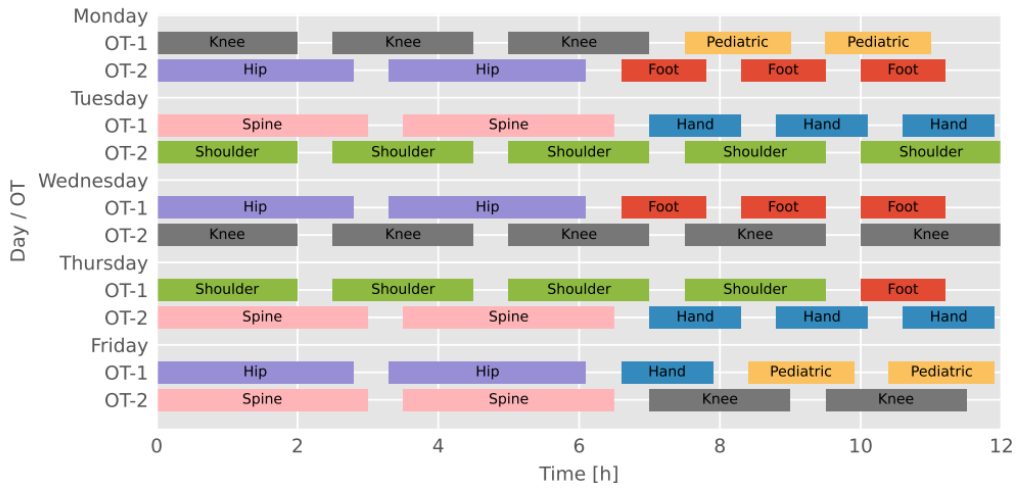


Figure 4.1: Weekly MSS for experiment A1.

Table 4.8 summarises the performance indicators discussed above for experiments A1 to A5, along with the value of the objective function, the (optimality) gap and the time in seconds required to search for solutions.

Table 4.8: Performance indicators for experiments A1 to A5.

Experiment	Time assigned for surgeries (h)	Total length of the OT sessions (h)	Weekly surgeries	Objective Function (O F)	Overall occupation rate (%)	Gap (%)	Computational time in seconds
A1	96.3	115.8	49	56.3	96.5	1.95	505
A2	104.9	126.4	54	63.9	95.8	1.88	1335
A3	113.3	136.8	59	69.3	95	1.88	6826
A4	114.5	138	60	71.5	88.5	0	2679
A5	116	139.5	61	73	83	1.92	1633

The results in Table 4.8 illustrate the effect of increasing the capacity for a fixed demand. As expected, as we add more OT capacity, the *overall occupation rate*

decreases, once the demand is kept constant in experiments A1-A5. To illustrate the changes, Figures 4.2 and 4.3 show the weekly MSS for experiments A4 and A5. Indeed, one can see in Figure 4.2 a considerable decrease in occupation on Wednesday and Thursday with respect to the MSS of experiment A1 (Fig. 4.1), whereas Figure 4.3 unfolds an additional decrease in OT occupation on Friday.

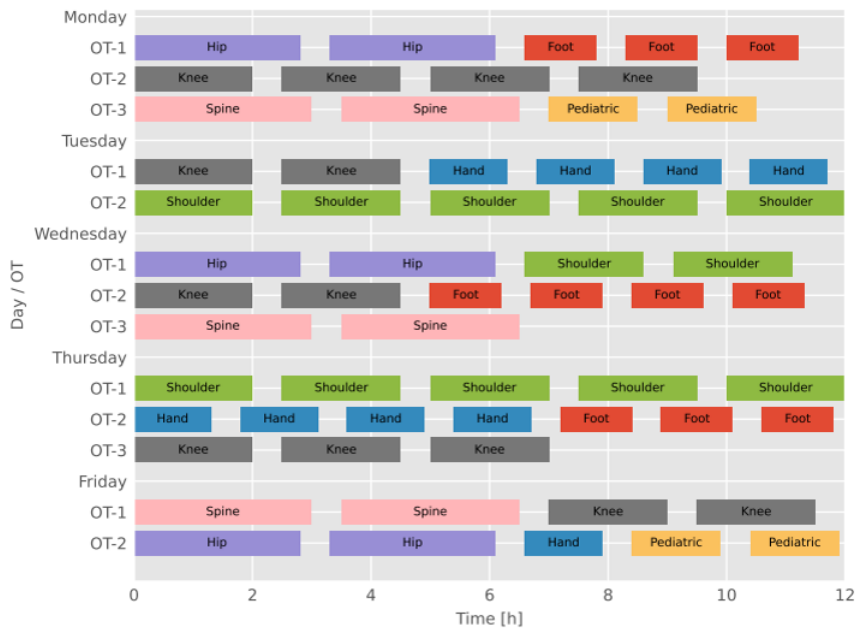


Figure 4.2: Weekly MSS for experiment A4.

Figure 4.4 shows the total number of surgeries for each speciality for experiments A1-A5. As expected, one can see a gradual increase in the number of surgeries as more OT capacity is added, up to the time each speciality reaches the respective upper bound in the number of surgeries, see Table 4.6. It is worth mentioning that the number of weekly surgeries for spine and hip already reach the upper bound in experiment A1 and remain there across all experiments.

To further explore the results, Figure 4.5 the total number of weekly surgeries as well as the overall time assigned for surgeries for all experiments. As expected, one can see that both quantities grow together as the OT capacity increases. Figure 4.6 shows the overall occupation rate for experiments A1-A5, depicting the decrease in the occupation rate as OT capacity is increased.

We will now analyse the effect of the increase in OT capacity in the bed allocation

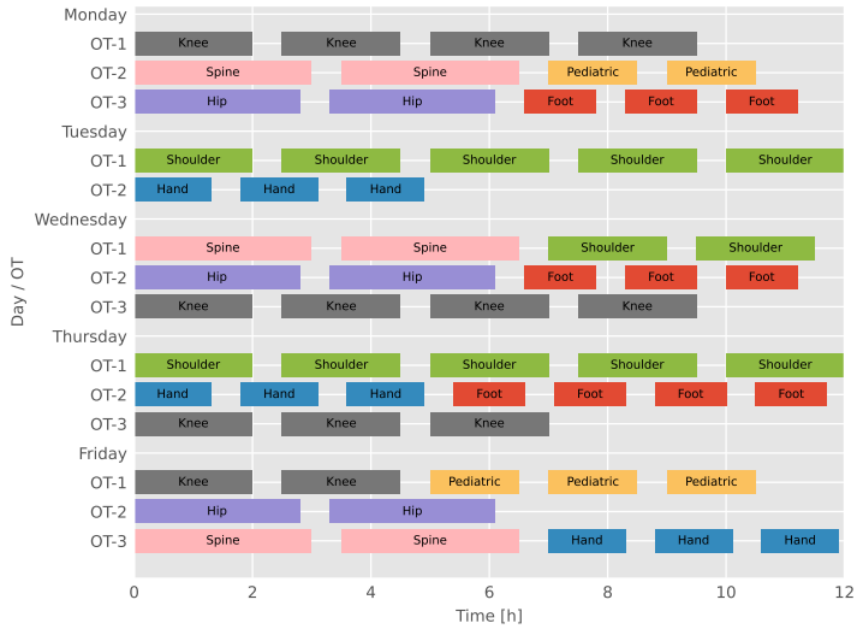


Figure 4.3: Weekly MSS for experiment A5.

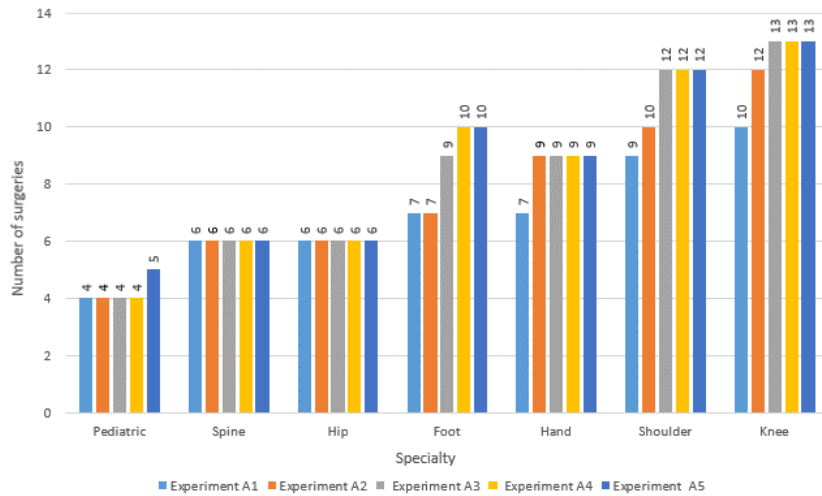


Figure 4.4: Weekly surgeries for experiments A1-A5.

for ICU, SICU and Ward. Figure 4.7 depicts the bed allocation to surgical specialties across the three post-surgical units for experiment A1. One can see that the largest number of ICU beds are allocated to hip and spine; this is expected considering that these specialties feature the longest length of stay in the ICU (Table 4.4) as well the largest likelihood of requiring an ICU bed (Table 4.5). Notice that shoulder and

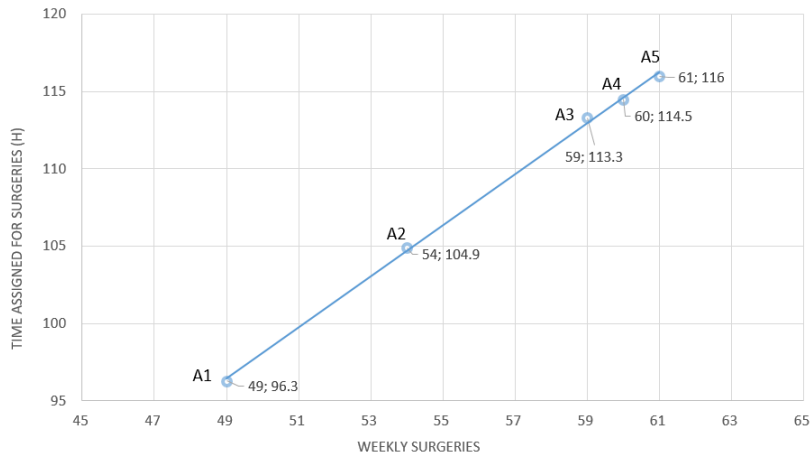


Figure 4.5: Weekly surgeries for experiments A1-A5.

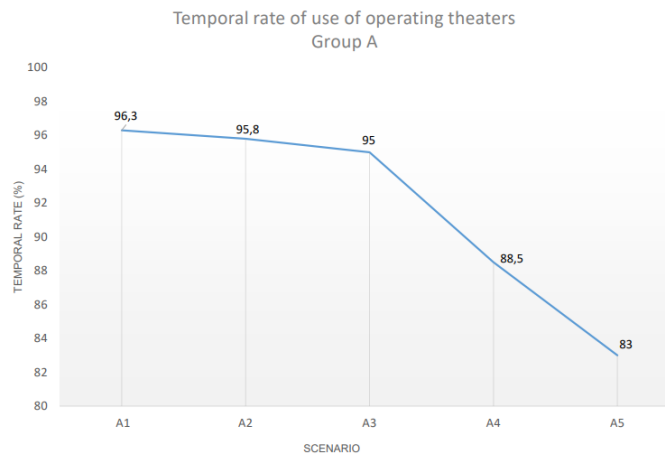


Figure 4.6: Overall occupation rate (%) for experiments A1-A5.

knee require more Ward and SICU beds due to the large weekly demand, whereas hip and spine have lower demands but still require a considerable number of Ward and SICU beds due to their extended lengths of stay.

Depicted in Figure 4.8, the bed allocation for experiment A5 requires a larger number of post-surgical beds across all three units. This is expected, as this is the experiment with the largest operating theatre capacity. Note that, for experiment A5, we need to allocate a total of 15 beds in the ICU, one unit less than the amount provided by the hospital, as shown in Table 4.5.

Finally, Figure 4.9 illustrates the change in the overall number of beds allocated

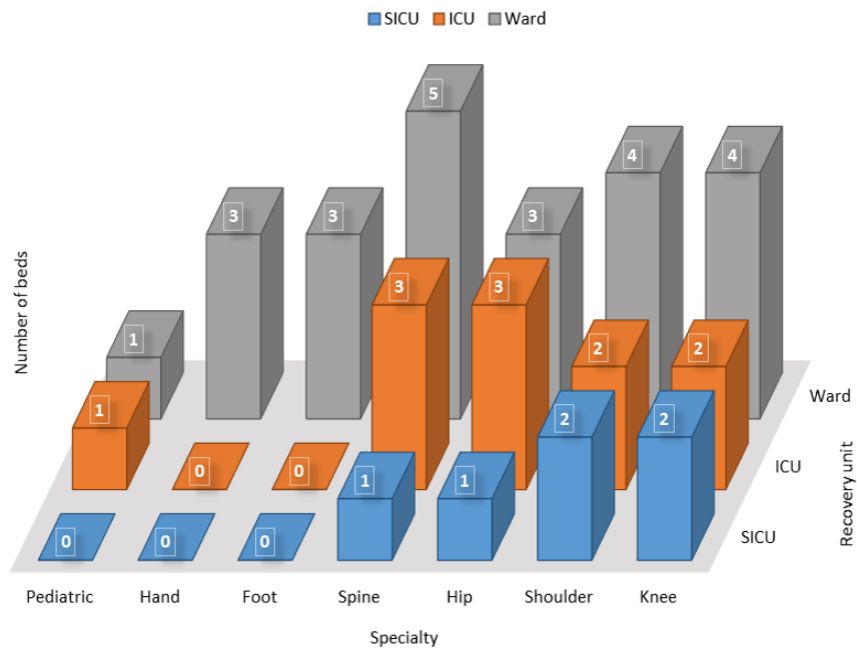


Figure 4.7: Post surgical bed allocation for experiment A1.

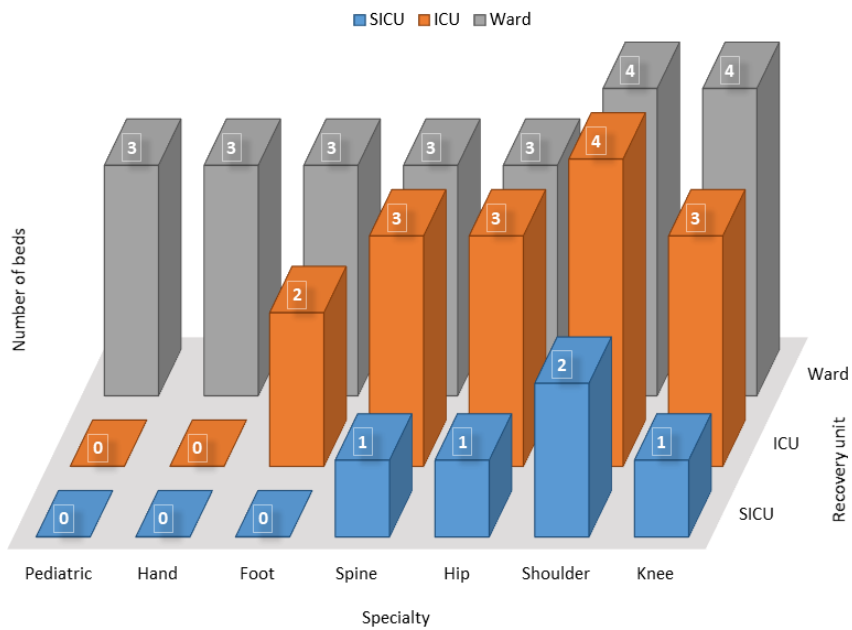


Figure 4.8: Post surgical bed allocation for experiment A5.

across the post-surgical units for experiments A1-A5. One can see a stable behaviour in the Ward and SICU, with a gradual increase in the required number of ICU beds

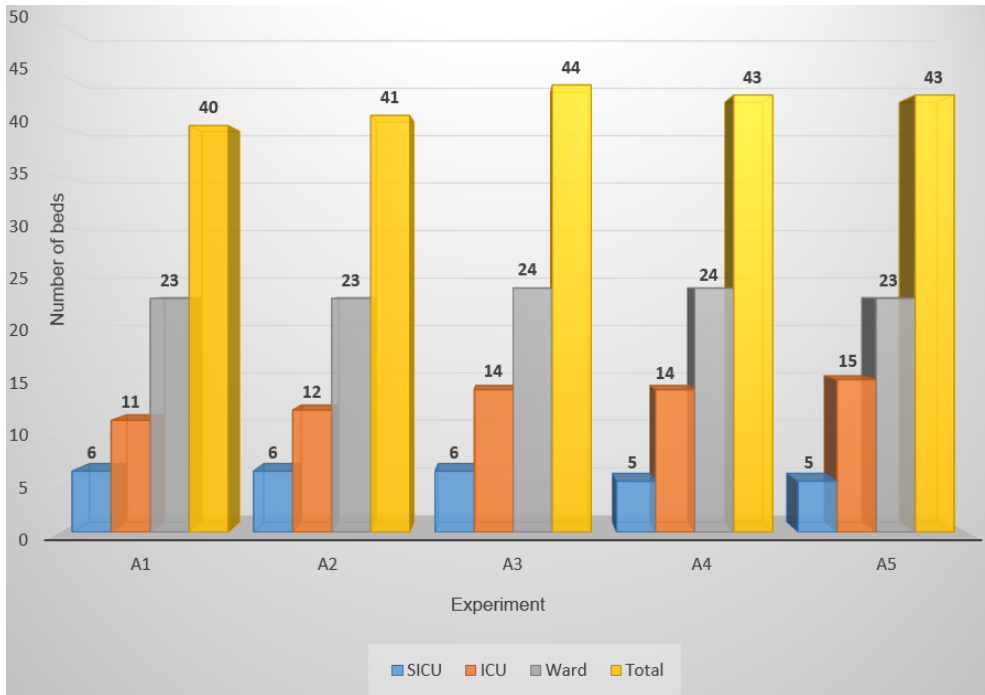


Figure 4.9: Beds allocated by recovery unit for experiments A1-A5.

as the OT capacity increases.

In the next section, we analyse the necessary resource capacity to balance supply and increased demand.

4.3 The effect of increases in weekly demand for surgeries

To investigate the sensitivity of the model with respect to demand increase, we evaluated the effect of demand increases of 20%, 40%, 60% and 100% with respect to the baseline. For each demand increase, we gradually increase operating theatre availability and observe the effects of the increase on the resulting optimal weekly surgery schedule and bed allocation plans across the ICU, the SICU and the Ward. In each analysis, the first experiment represents the minimum number of OTs required to attain a feasible solution, and the last experiment represents the enough OT capacity to approach the upper bound in the number of surgeries for each speciality.

The OT capacity and the demand multipliers (with respect to Table 4.4) for the resulting experiments are depicted in Table 4.9. The bed capacities and remaining parameters maintained the baseline values from experiments A1-A5, except for the experiments D7, E10, E11 and E12, where more beds were required in the ICU to approach the upper bound in the number of surgeries for each speciality. One can see that we may need to roughly double the capacity of the OT with respect to the baseline to accommodate an increase of 100% in the surgery demand levels across all specialties.

Table 4.9: Experiments B1 to E12.

Experiment	Parameter W	Number of operating theatres required					Demand
		Monday	Tuesday	Wednesday	Thursday	Friday	
B1	1	3	2	2	2	2	1.2 * Dem_s
B2		3	3	2	2	2	
B3		3	3	3	2	2	
B4		3	3	3	3	2	
C1	1	3	3	3	2	2	1.4 * Dem_s
C2		3	3	3	3	2	
C3		3	3	3	3	3	
C4		4	3	3	3	3	
C5		4	4	3	3	3	
D1	1	3	3	3	3	3	1.6 * Dem_s
D2		4	3	3	3	3	
D3		4	4	3	3	3	
D4		4	4	4	3	3	
D5		4	4	4	4	3	
D6		4	4	4	4	4	
D7		4	4	4	4	4	
E1	1	4	4	4	4	3	2 * Dem_s
E2		4	4	4	4	4	
E3		5	4	4	4	4	
E4		5	5	4	4	4	
E5		5	5	5	4	4	
E6		5	5	5	5	4	
E7		5	5	5	5	5	
E8		6	5	5	5	5	
E9		6	5	5	6	5	
E10		6	5	5	6	5	
E11		6	5	5	6	6	
E12		6	5	5	6	6	

Table 4.10 shows the performance indicators for each of the experiment in Table 4.9. As expected, we observe increases in the number of surgeries as OT capacity increases, with a corresponding decrease in the OT occupation.

Figures 4.10, 4.11, 4.12 and 4.13 show the total number of weekly surgeries scheduled for each speciality in experiments B1-B4, C1-C5, D1-D7 and E1-E12, together with the weekly demand and the upper bound in the number of weekly surgeries.

Figures 4.14, 4.15, 4.16 and 4.17 illustrate the effect of the demand increase on

Table 4.10: Performance indicators for experiments B1 to E12.

Experiment	Time assigned for surgeries (h)	Total length of the OT session (h)	Weekly surgeries	Objective Function (O F)	Overall occupation rate (%)	Gap (%)	Computational time in seconds
B1	105.5	127.5	55	60.5	96.6	1.93	5253
B2	114.1	138.1	60	66.1	95.9	1.98	4258
B3	124.3	150.3	65	72.3	95.2	1.96	6890
B4	128	155	68	76	92.3	1.99	5852
C1	125.1	151.1	65	71.1	96.9	1.94	4232
C2	135.1	163.1	70	80.1	96.6	1.95	5023
C3	145.1	174.6	74	88.1	96.4	1.87	6031
C4	150.2	181.2	78	92.2	94.4	1.74	4821
C5	154.1	186.1	81	93.1	91.2	1.98	4069
D1	144.6	174.6	75	85.6	97	1.99	5631
D2	153	185	80	92	96.4	1.91	7036
D3	157.3	189.8	82	95.3	93	1.89	5021
D4	165	199	86	100	92.1	1.94	3042
D5	168	203	89	104	89	1.91	3448
D6	170.6	206.1	91	106.6	85.9	1.95	2746
D7	172.6	208.6	92	107.6	86.9	1.89	4068
E1	169.7	204.2	88	103.7	89.6	1.98	1536
E2	179.2	215.7	93	111.2	89.3	1.88	1428
E3	183.1	220.6	96	116.1	87.5	1.97	1368
E4	190	229	100	120	86.7	1.95	1042
E5	193.9	233.9	103	123.9	84.7	1.97	1011
E6	196.9	237.4	105	126.9	82.4	1.99	702
E7	199.3	240.3	107	130.2	80.1	1.93	90
E8	201.9	243.4	109	132.9	78	1.95	43
E9	201.9	242.9	109	132.9	75	1.97	34
E10	207.9	250.4	112	138.9	77.3	1.94	31
E11	207.9	249.4	111	137.9	74.2	1.95	26
E12	213.9	256.9	114	138.9	76.5	0.8	20

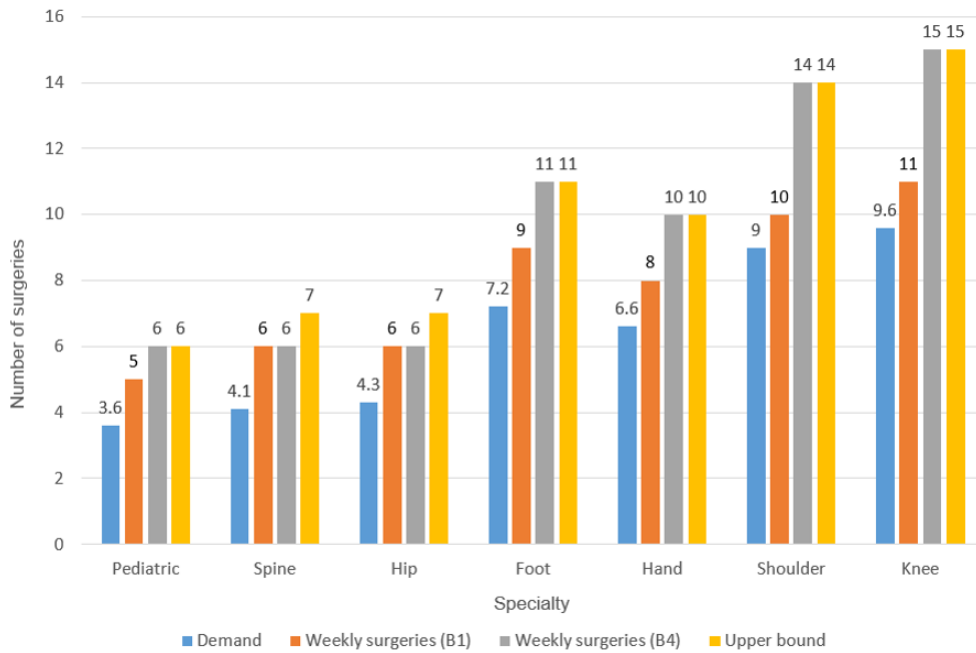


Figure 4.10: Demand, weekly surgeries and upper bounds for experiments B1-B4.

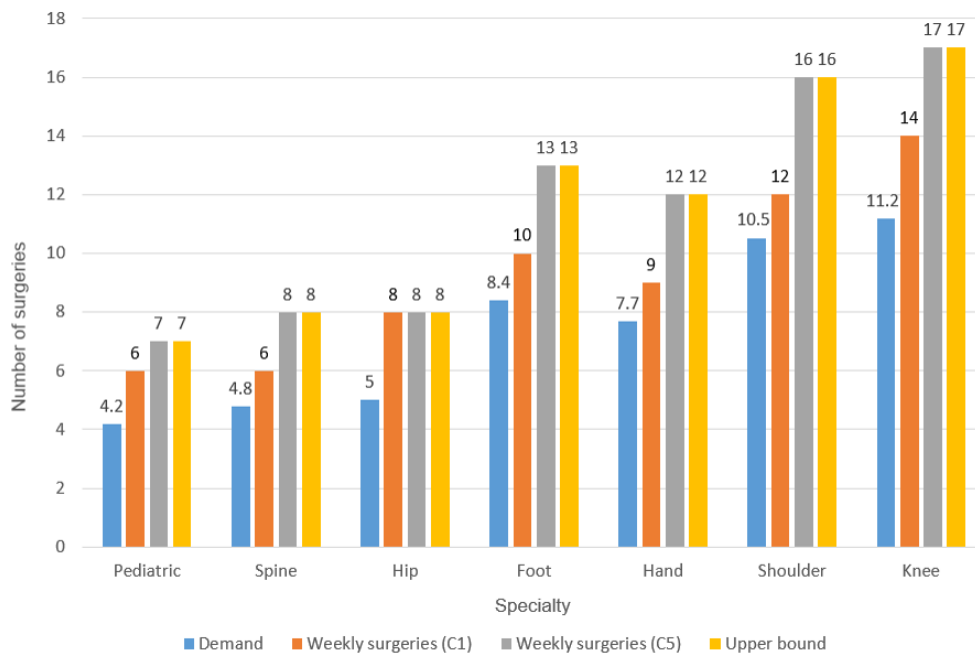


Figure 4.11: Demand, weekly surgeries and upper bounds for experiments C1-C5.

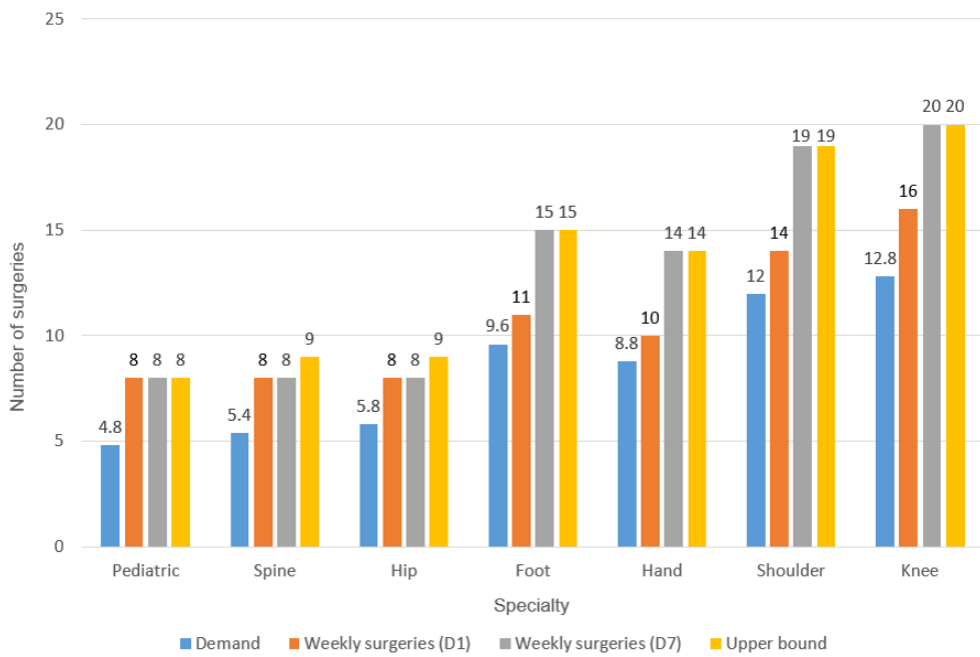


Figure 4.12: Demand, weekly surgeries and upper bounds for experiments D1-D7.

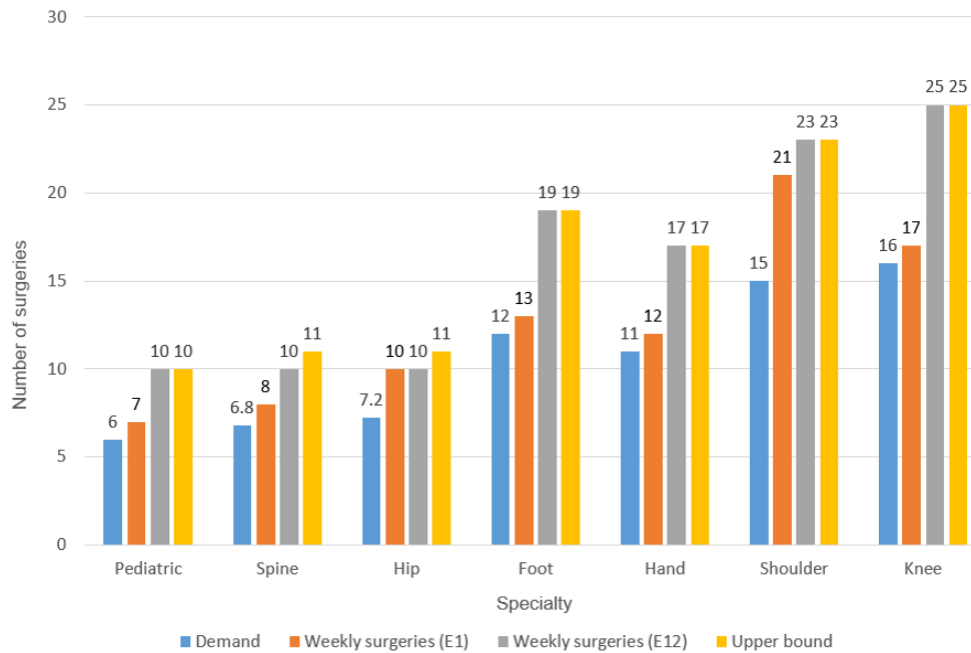


Figure 4.13: Demand, weekly surgeries and upper bounds for experiments E1-E12.

the number of beds allocated in ICU, SICU and Ward. One can notice a significant increase in the number of required ICU and Ward beds as demand increases. The level of SICU beds, however, is kept stable as the overall probability of using SICU beds is generally small across most specialties, with short projected lengths of stay. Overall, while experiment B1 employs 45 post-surgical beds, experiment E12 requires 70 beds; which amounts to an increase of 55%.

In experiments D1-D7 and E1-E12, where we observe, respectively, increases of 60% and 100% concerning the original demand, the current availability of beds in each recovery unit (Table 4.5) corresponds to the volume of surgeries required to meet the demand. However, to reach the upper bound in the number of surgeries, we needed necessary to add one and two units respectively to the current amounts in the ICU.

Figures 4.18 and 4.19 show the demand, weekly surgeries and upper bounds for experiments D6 and D7, respectively. The upper bound for knee speciality was only reached in experiment D7 after the addition of one bed in the ICU, necessary to assign one remaining surgery. Figures 4.20 and 4.21 show the MSS for the referred experiments.

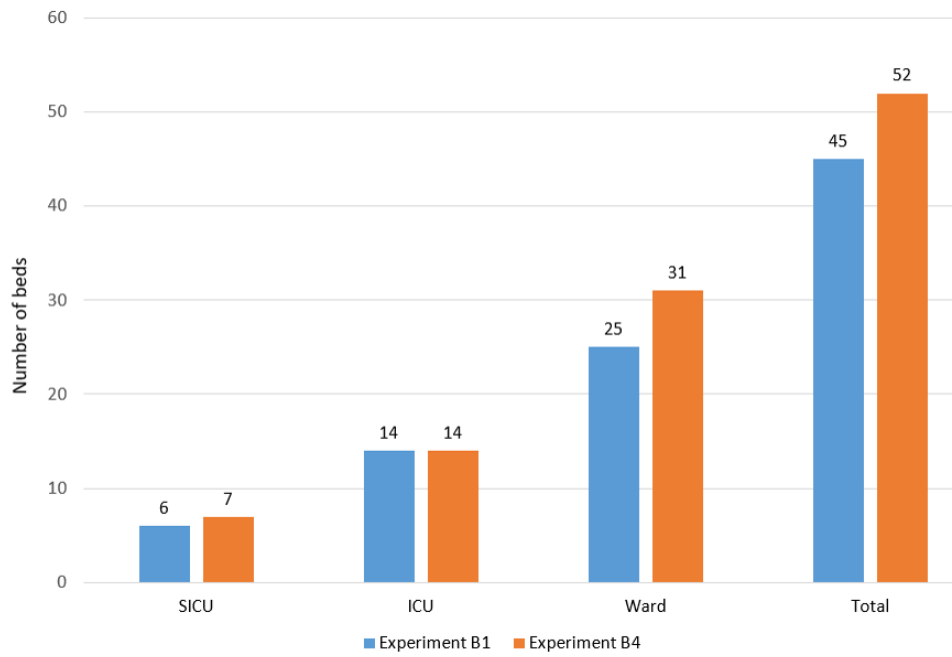


Figure 4.14: Beds allocated for experiments B1-B4.

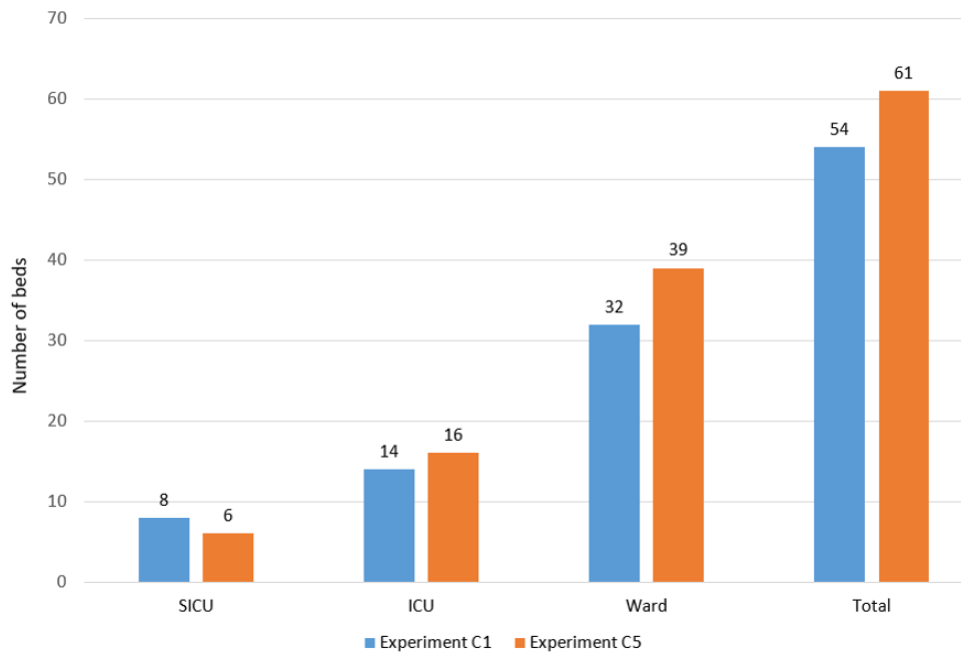


Figure 4.15: Beds allocated for experiments C1-C5.

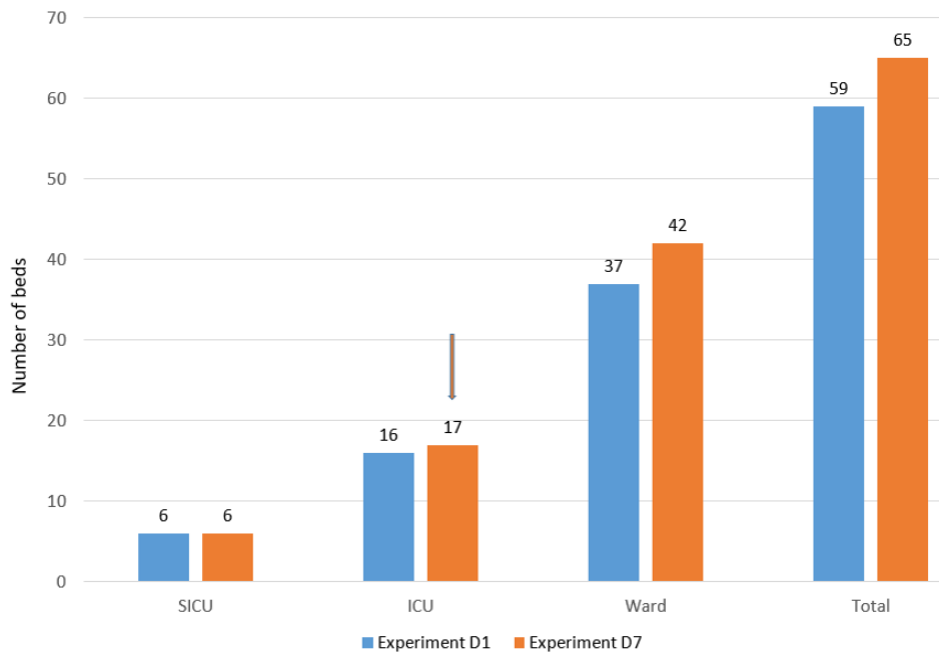


Figure 4.16: Beds allocated for experiments D1-D7.

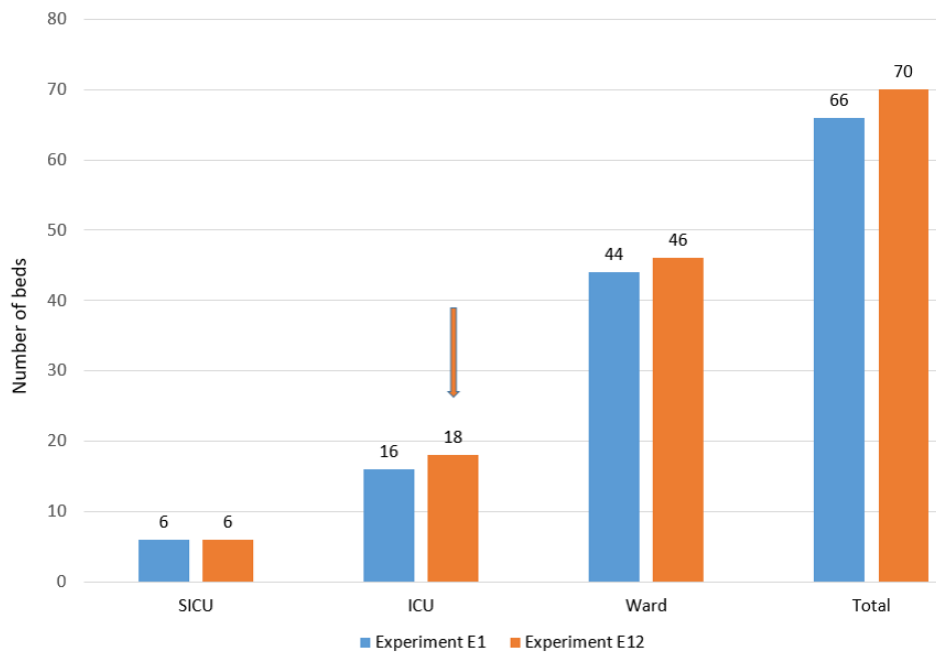


Figure 4.17: Beds allocated for experiments E1-E12.

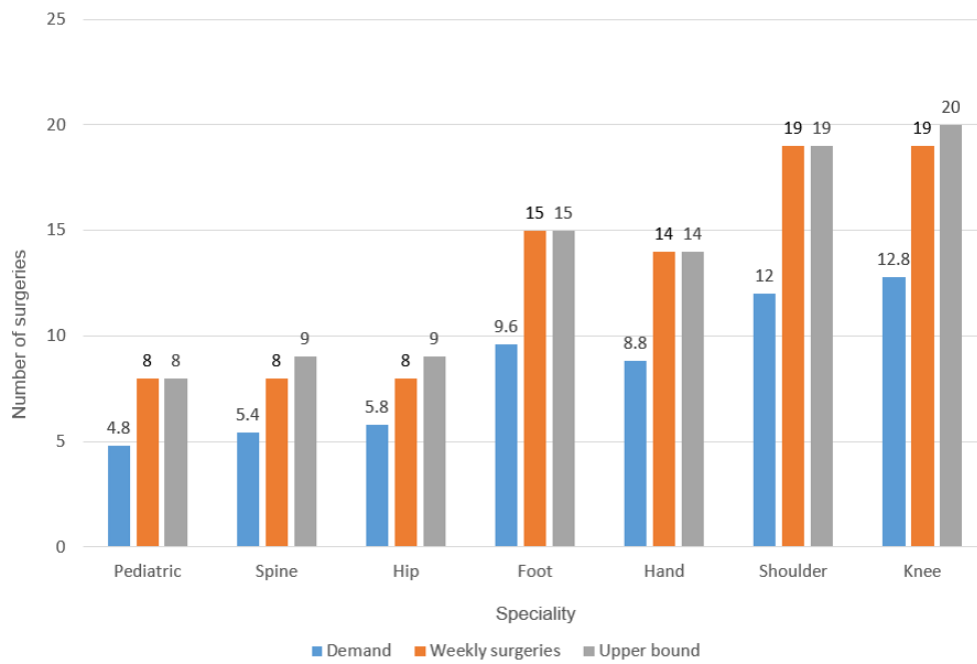


Figure 4.18: Demand, Weekly surgeries and upper bound for experiment D6.

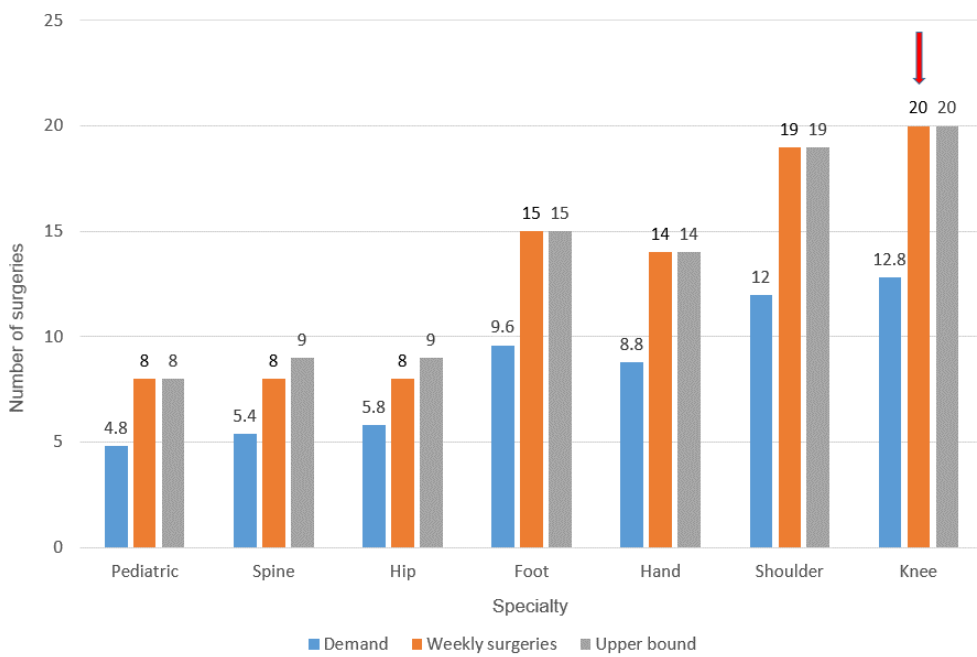


Figure 4.19: Demand, Weekly surgeries and upper bound for experiment D7.

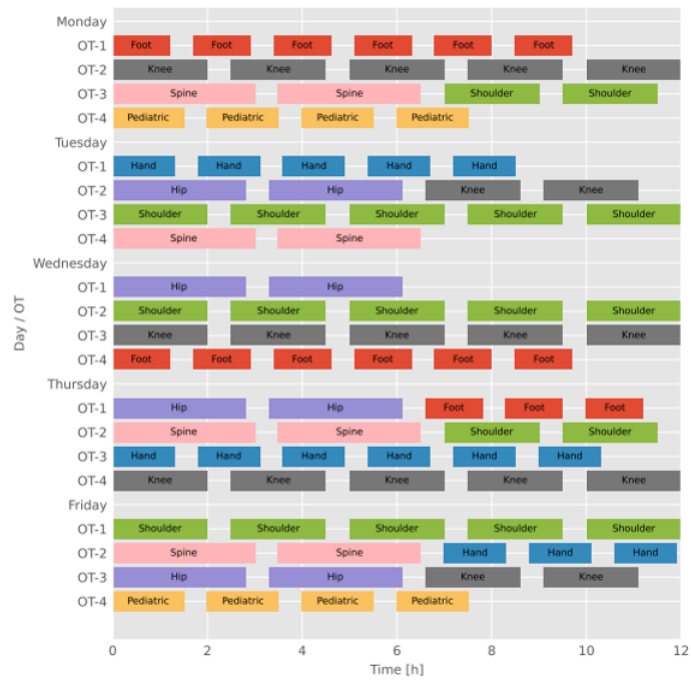


Figure 4.20: MSS for experiment D6.

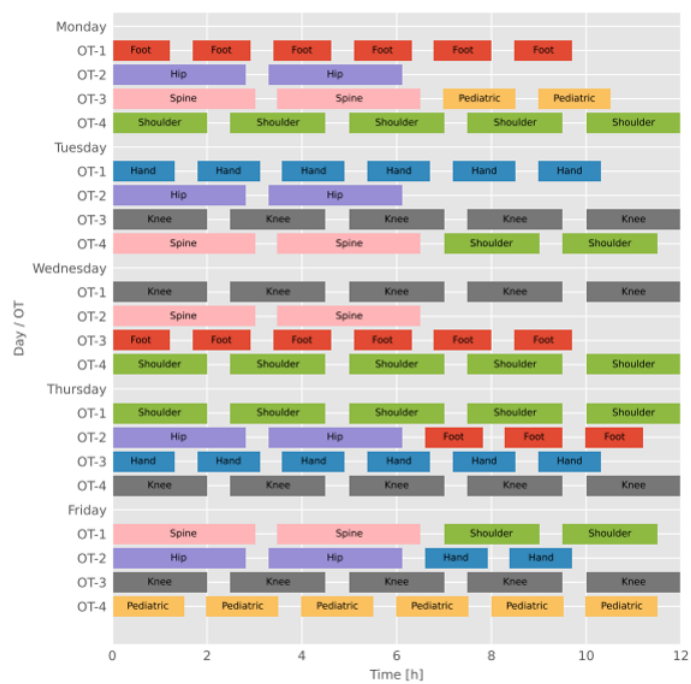


Figure 4.21: MSS for experiment D7.

For experiments E10 and E11, the addition of one bed in the ICU is still not enough to reach the upper bound for all specialities. Observe in the Figure 4.22 that the upper bound of the speciality spine is reached only for experiment E11 and for the speciality shoulder only for experiment E10. For experiment E12 (Figure 4.23), after the addition of one more bed in the ICU, in a total equal to 18 units, the upper bounds are reached for all specialities.

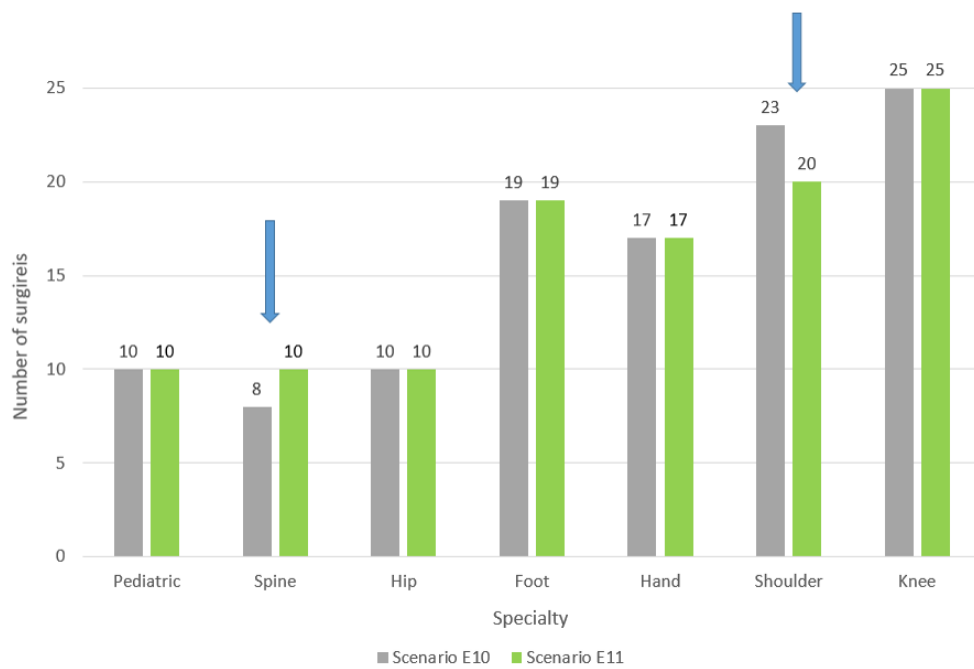


Figure 4.22: Weekly surgeries and upper bound for experiments E10-E11.

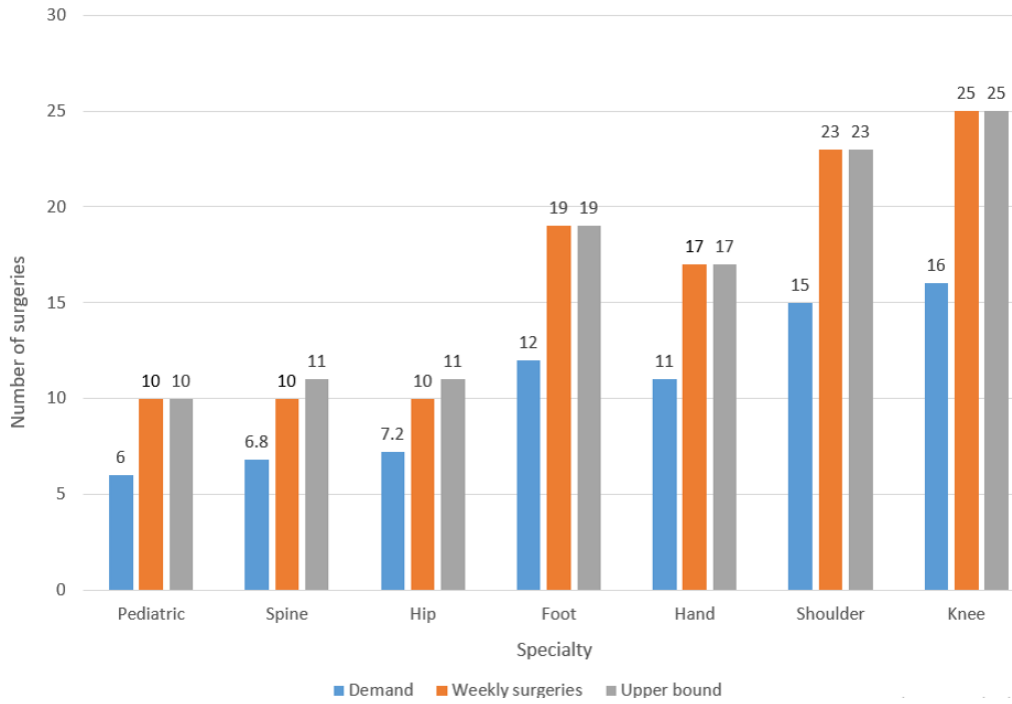


Figure 4.23: Demand, weekly surgeries and upper bound for experiment E12.

For the increase of 100% in demand, in the spine and hip specialties, although the product $1.5 * Dem_s$ has integer part equal to 11, the maximum value achieved is equal to 10, since the number of surgeries is divided equally between procedures requiring recovery in the ICU and the SICU (Table 4.4).

Finally, Figure 4.24 illustrates the total number of beds allocated in the post-surgical units for experiment E12 in each specialty. The largest amounts are allocated to hip and spine specialties in the ICU.

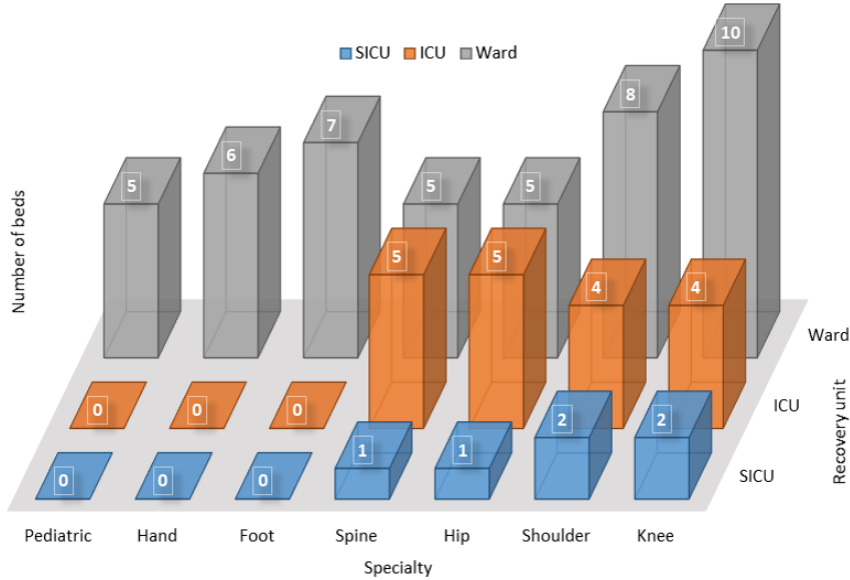


Figure 4.24: Post surgical bed allocation for experiment E12.

In the next section, we analyse the effect of the penalty in the number of allocated beds.

4.4 The effect of the penalty in the number of allocated beds

Recalling that parameter W in the objective function (eq. (3.1)) effectively penalises the allocation of post-surgical beds in the final solution, this section proposes a set of experiments to assess the effect of this parameter on the allocation of ICU, SICU and Ward beds. To do that, we introduce experiments F1-F9, based on the OT availability of experiment A4 (Table 4.7) of section 4.2.

Table 4.11 conveys the results from experiments F1-F9, which cover different values of the penalty parameter W . Observe that all available beds across SICU, ICU and the Ward are allocated when $W = 0$. This is expected, as no penalty is considered for allocating beds to specialities, therefore one can expect the spare bed capacity to be distributed across the medical specialities. The same behaviour is observed for small values of W , as one can see that the number of assigned surgeries

and the total time assigned for surgeries remain constant up to $W = 0.7$. As W increases, however, one can expect a decrease in the number of allocated beds, which in turn results in a decrease in the number of performed surgeries and therefore in the total time assigned for surgeries. This is observed in Table 4.11, as these quantities display a non-increasing behaviour with respect to parameter W , until they reach a lower limit. Indeed, one can see that the solutions remain constant for $W \geq 6.1$. This can be expected in general, as for large values of W one can expect the optimal solution to allocate the minimum number of SICU, ICU and Ward beds that ensure that the weekly schedule includes the minimum number of surgeries to satisfy and exceed the weekly demand by one unit - eq. (3.6).

Table 4.11: Experiments F1 to F9 and performance indicators.

Experiment	Parameter W	Results					
		Time assigned for surgeries (h)	Weekly surgeries	Beds allocated	Objective Function (O F)	Gap (%)	Computational time in seconds
F1	0	116	61	124	116	0	10
F2	0.5	116	61	45	93.5	0.3	12
F3	0.7	116	61	45	84.5	0.1	16
F4	0.8	114.5	60	43	80.1	0	19
F5	0.9	114.5	60	43	75.8	0	19
F6	5	105.5	54	38	-84.5	0.2	30
F7	6	105.5	54	38	-122.5	0	15
F8	6.1	99.5	51	37	-126.2	0	11
F9	10	99.5	51	37	-270.5	0	14

Figure 4.25 summarises the evolution of the total time assigned for surgeries as we increase the penalty parameter W . It conveys the non-increasing behaviour of the total time assigned for surgeries with respect to W . One can see that the maximum number of surgery hours is observed for small values of W , and that the number of surgery hours gradually decreases as W increases, until we reach the minimum total number of SICU, ICU and Ward beds that are required to meet and exceed the demand, from where the weekly schedule will remain constant.

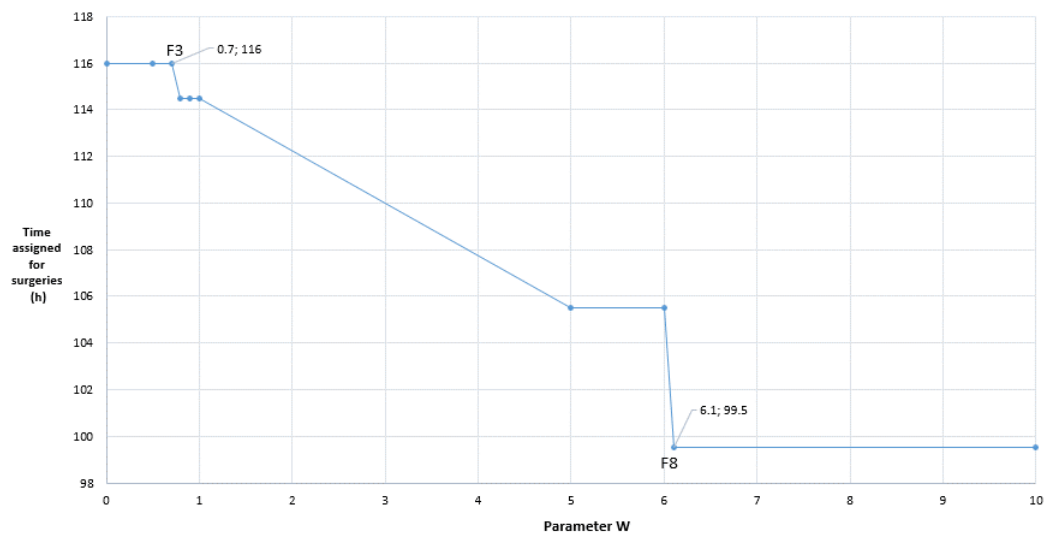


Figure 4.25: Evolution of weekly time assigned for surgeries with the penalty parameter W .

Chapter 5

Conclusions

This work introduced a general integrated surgery scheduling and post-surgical bed planning problem for a typical surgical centre configuration, including multiple surgery recovery units and multiple routes of post-surgical care. The approach allows the decision maker to not only design an optimised tactical surgery scheduling plan, but also to plan the post-surgical bed capacity in the intensive and semi-intensive care units and in the ward, to ensure patient flow and therefore prevent cancellations due to the unavailability of downstream resources, i.e., post-surgical care capacity.

Starting from the decision support required by the hospital partner, the model bridges the gap between theory and practice by providing support for tactical planning in a realistic hospital setting, with a level of generality not previously addressed in the literature. For each speciality, the model includes the probability that a patient will need either intensive or semi-intensive care and considers the maximum stay at these units, thereby providing some level of robustness in the bed planning. This is essential, as it helps us make sure that the downstream resources suffice to ensure patient flow and avoid cancellations.

The integrated model will allow decision makers to experiment with the parameters and find out the level of upstream and downstream resources need to satisfy the demand for all specialities, whilst considering the whole patient trajectory up to hospital discharge. Indeed, the demand and capacity constraints are designed to ensure service provision for all specialities, thereby linking with long-term goals such as to reduce waiting queues while ensuring service provision for all patients who demand it.

The healthcare modelling approach proposed in this work gives rise to a number of possible future research avenues. One obvious albeit challenging extension is to consider the uncertainty in either the surgery times or the lengths of stay in the ward. That would be a sensible step towards considering both sources of uncertainty. One can also investigate extensions of the proposed model for surgical centres subject to urgent or emergency surgeries. This is a challenging task as it would also involve the modelling of the protocol to be followed in case of an emergency or urgent surgical request, which would determine for example whether and which elective surgery would be cancelled to accommodate the extra demand, as well as the capacity sharing between elective and non-elective procedures for both upstream and downstream resources.

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Appendix A

Weekly MSS for experiments

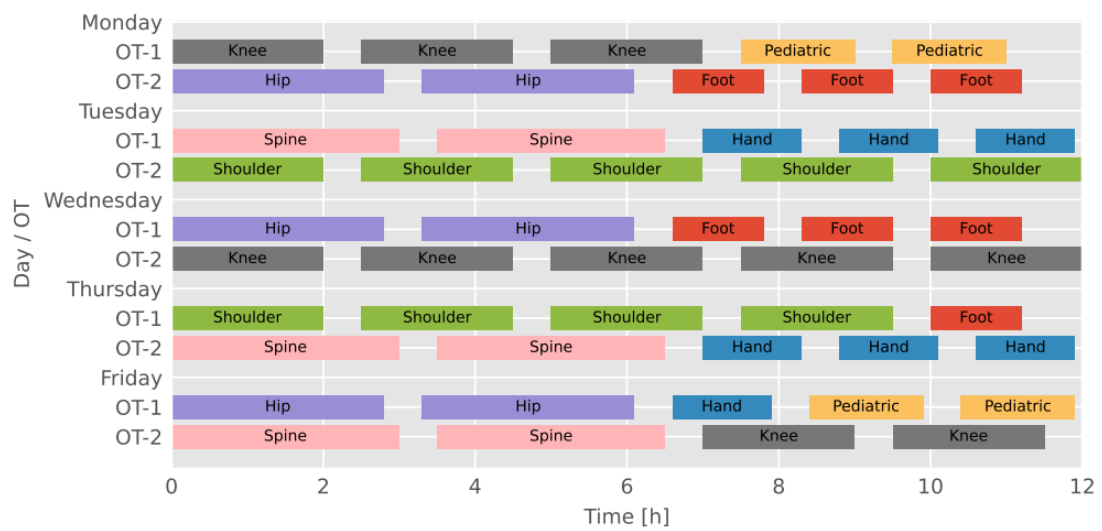


Figure A.1: Weekly MSS for experiment A1.

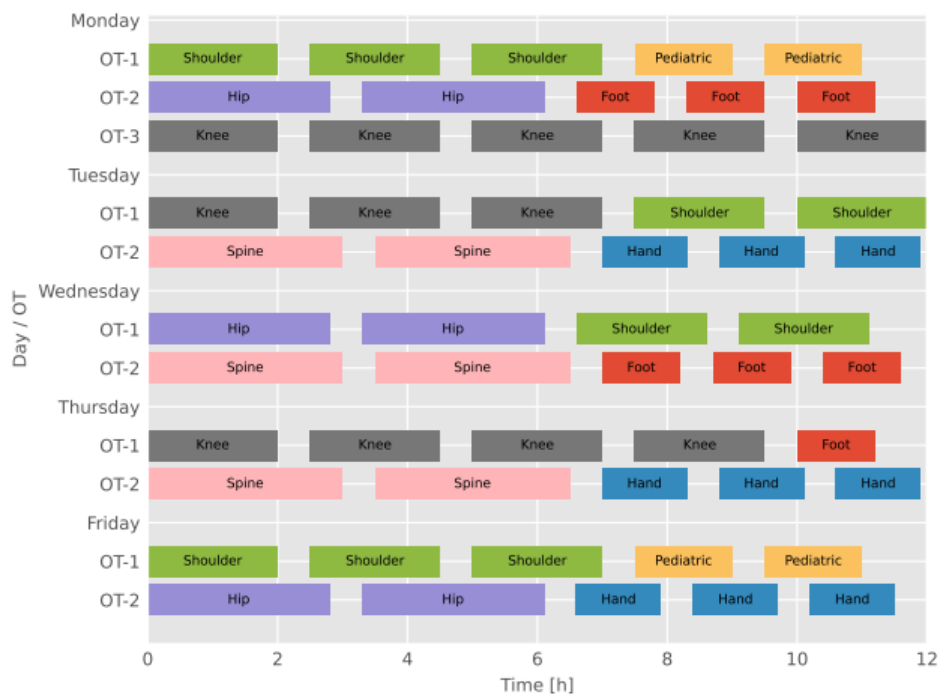


Figure A.2: Weekly MSS for experiment A2.

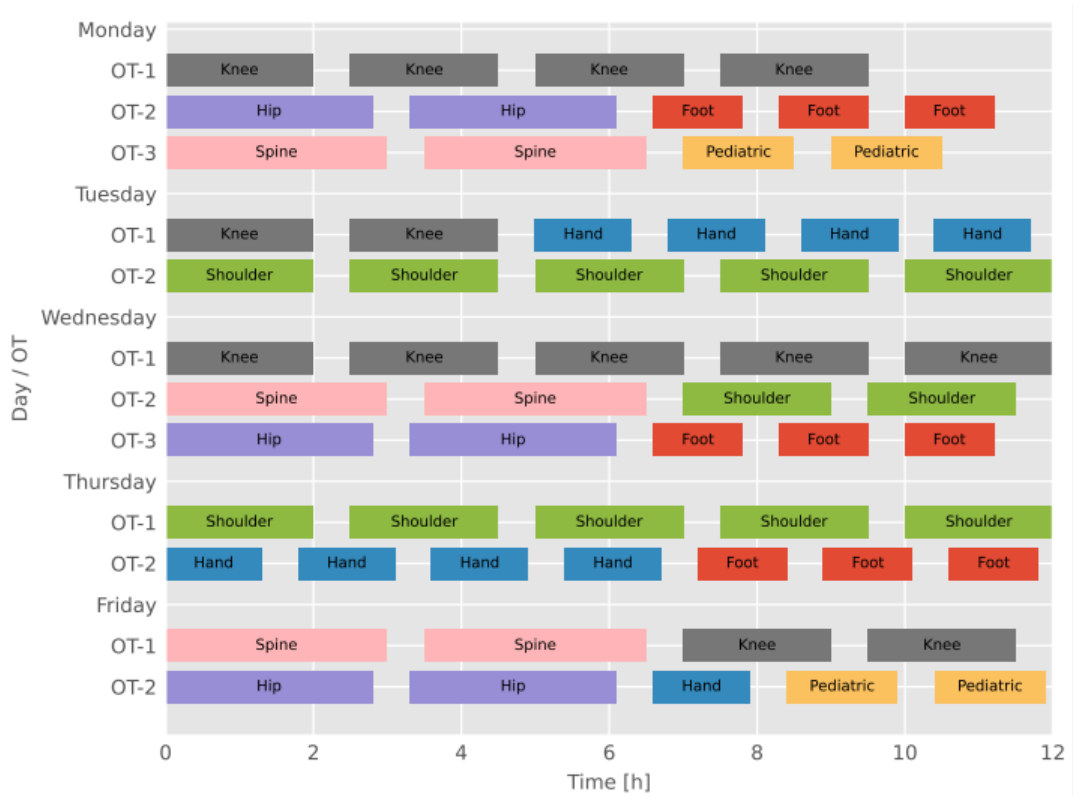


Figure A.3: Weekly MSS for experiment A3.

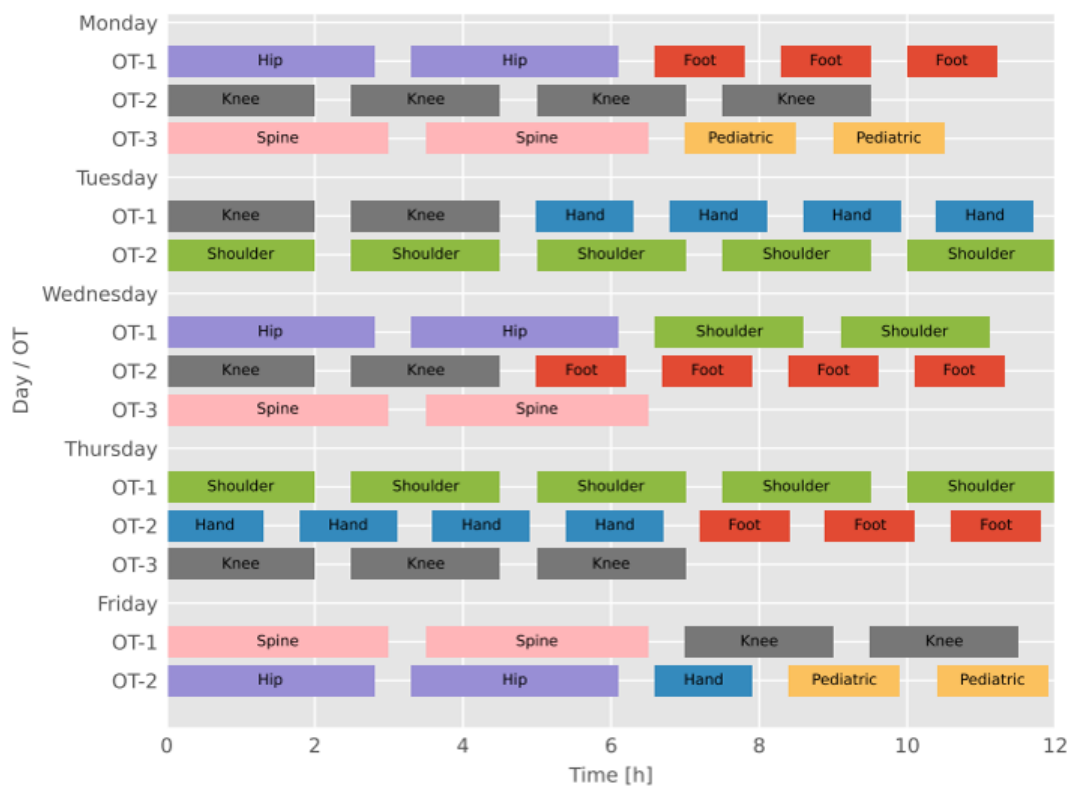


Figure A.4: Weekly MSS for experiment A4.

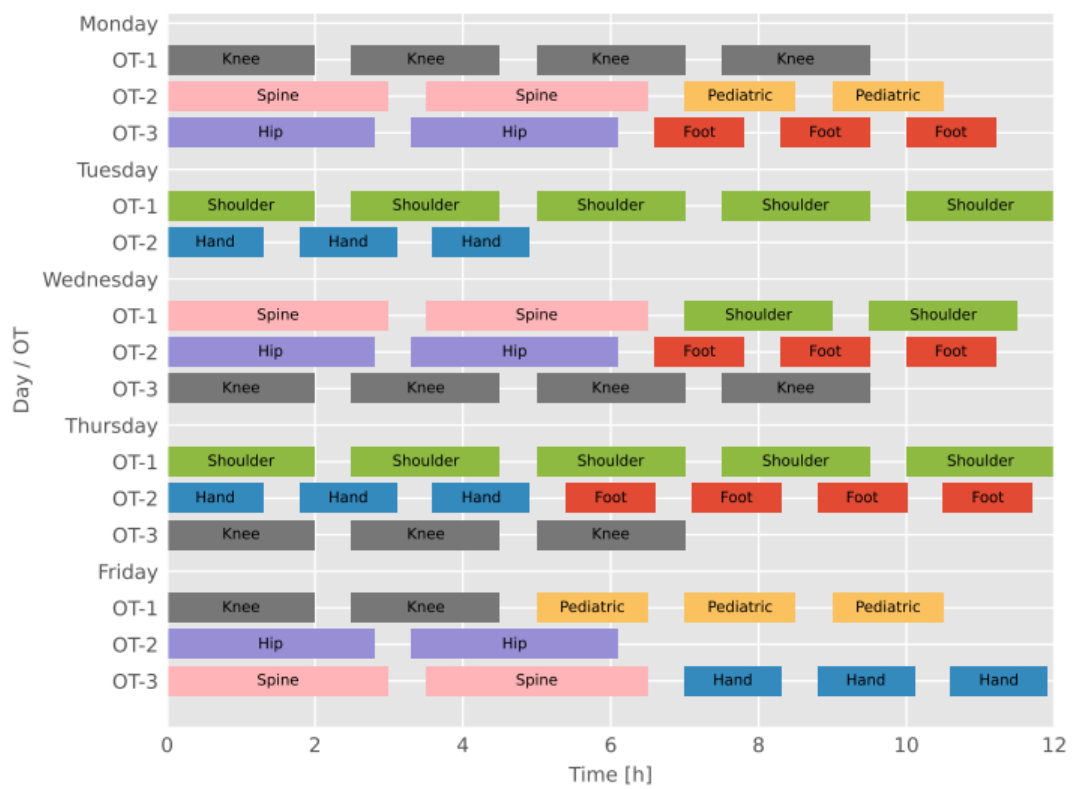


Figure A.5: Weekly MSS for experiment A5.

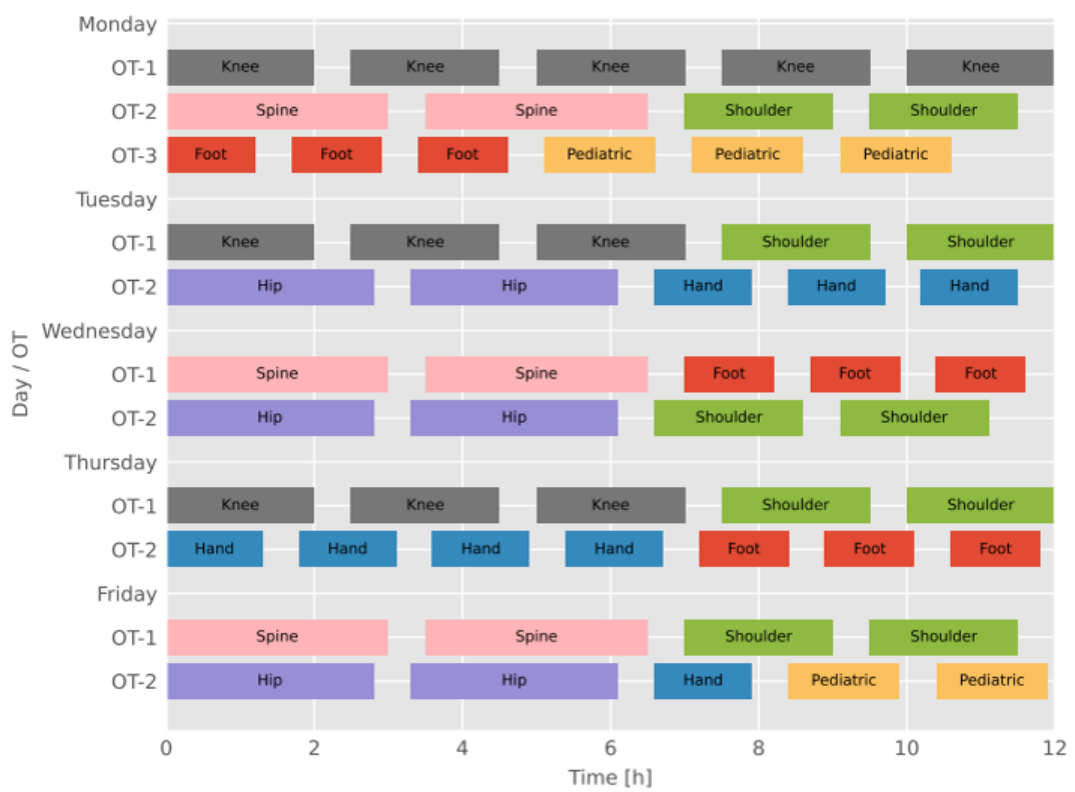


Figure A.6: Weekly MSS for experiment B1.

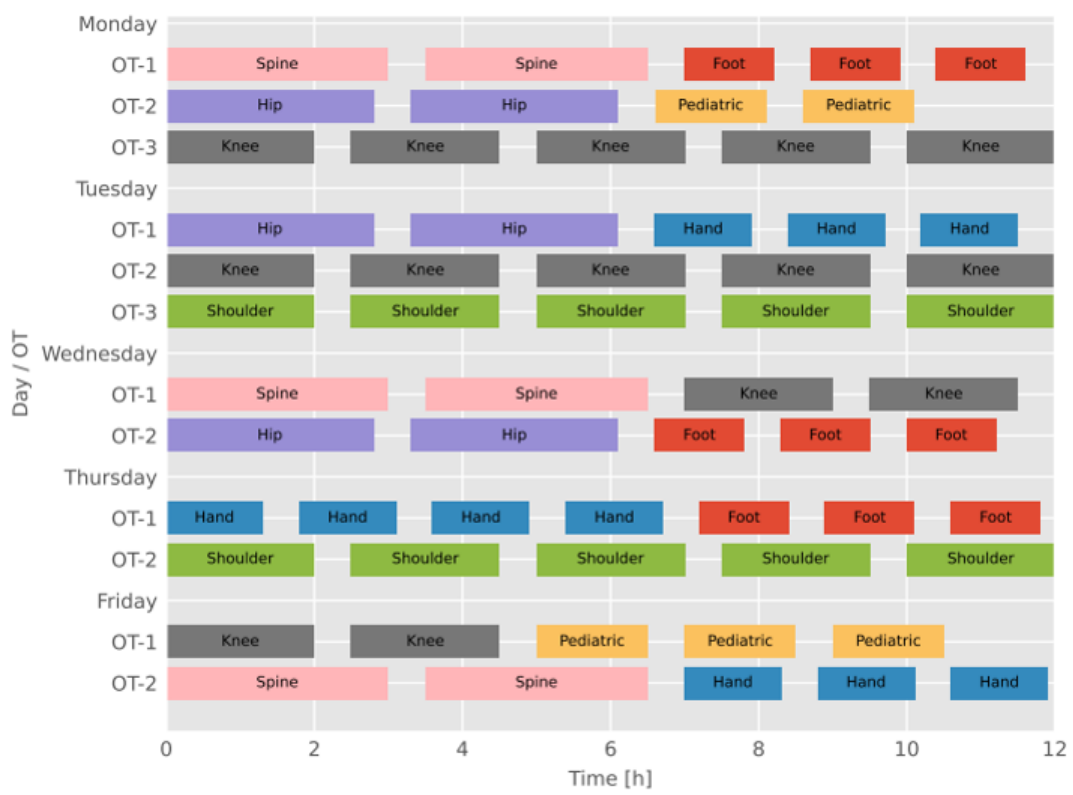


Figure A.7: Weekly MSS for experiment B2.

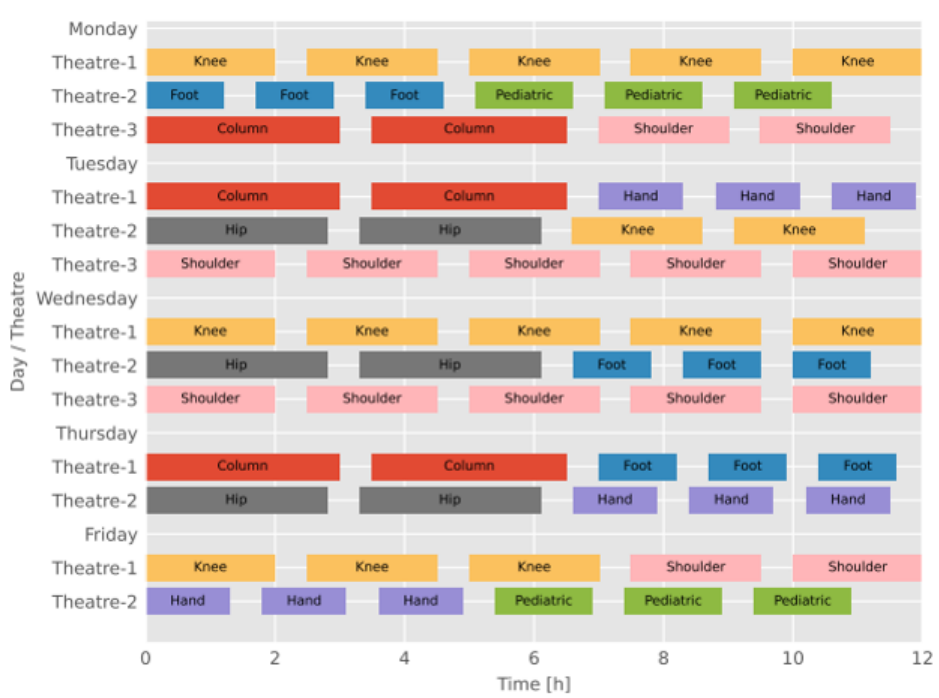


Figure A.8: Weekly MSS for experiment B3.

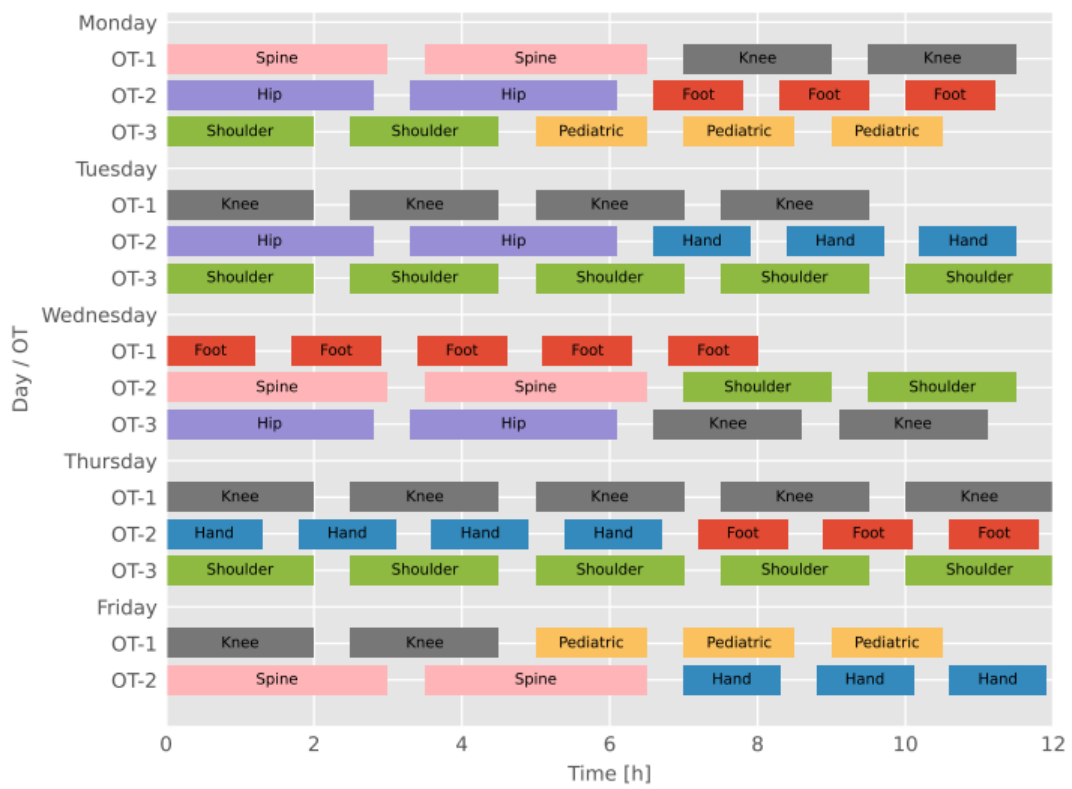


Figure A.9: Weekly MSS for experiment B4.

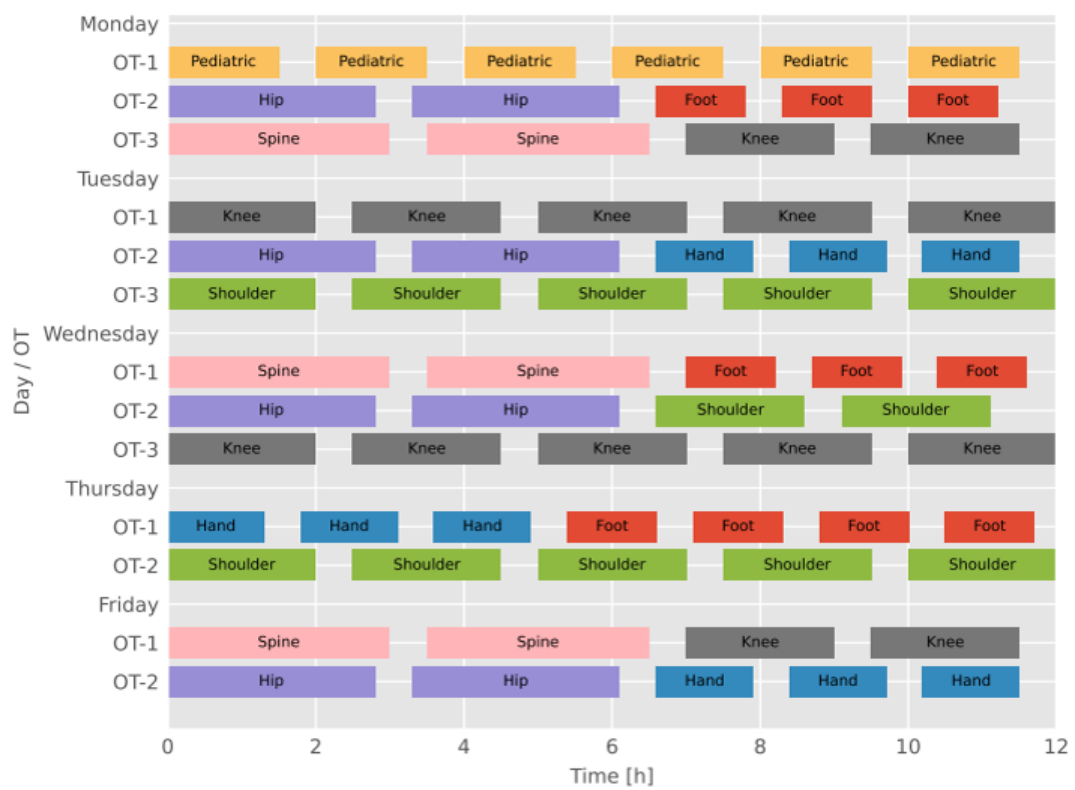


Figure A.10: Weekly MSS for experiment C1.

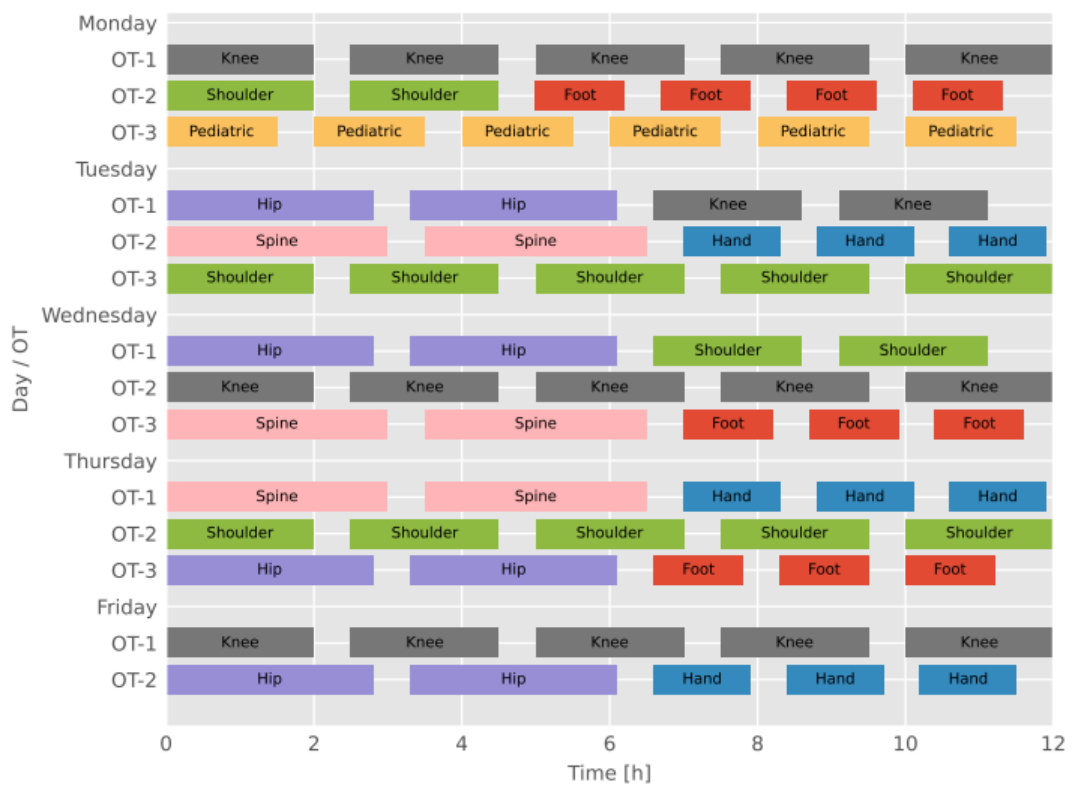


Figure A.11: Weekly MSS for experiment C2.

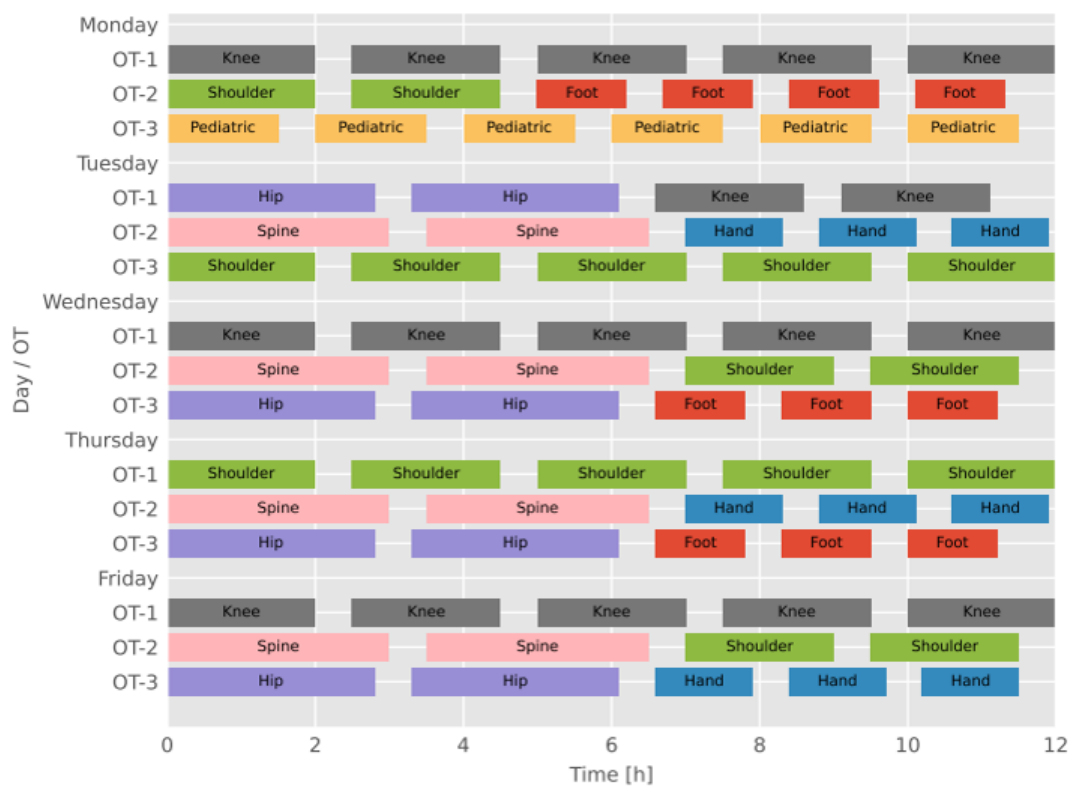


Figure A.12: Weekly MSS for experiment C3.

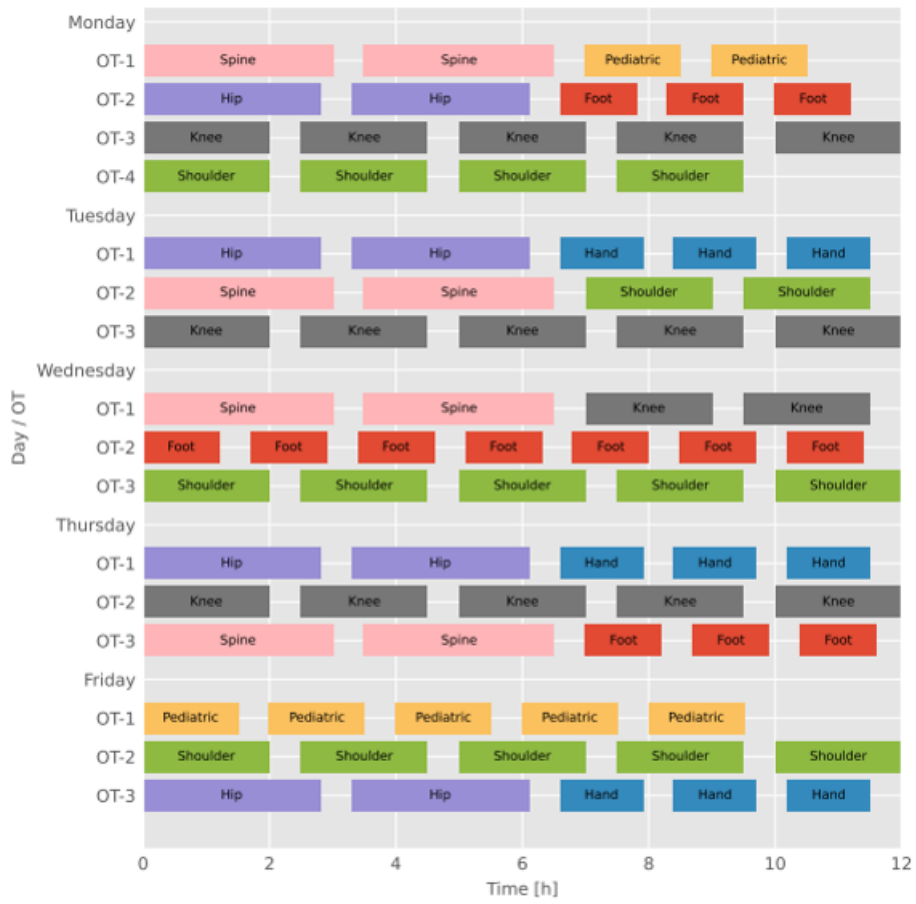


Figure A.13: Weekly MSS for experiment C4.

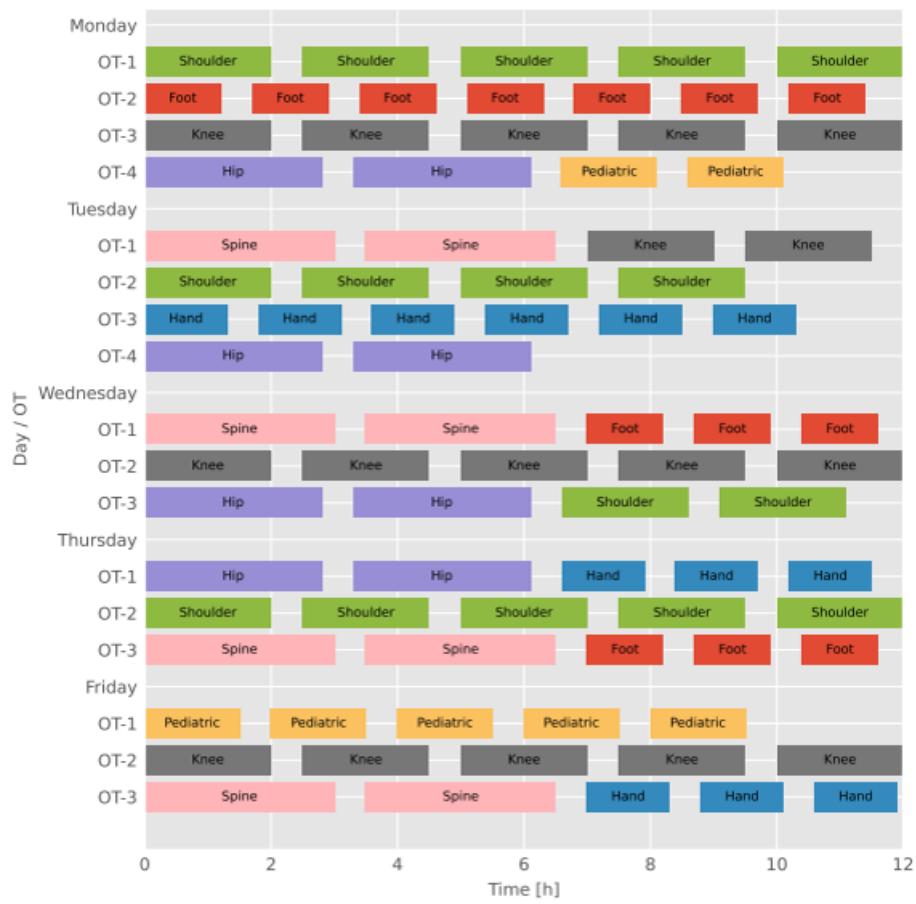


Figure A.14: Weekly MSS for experiment C5.

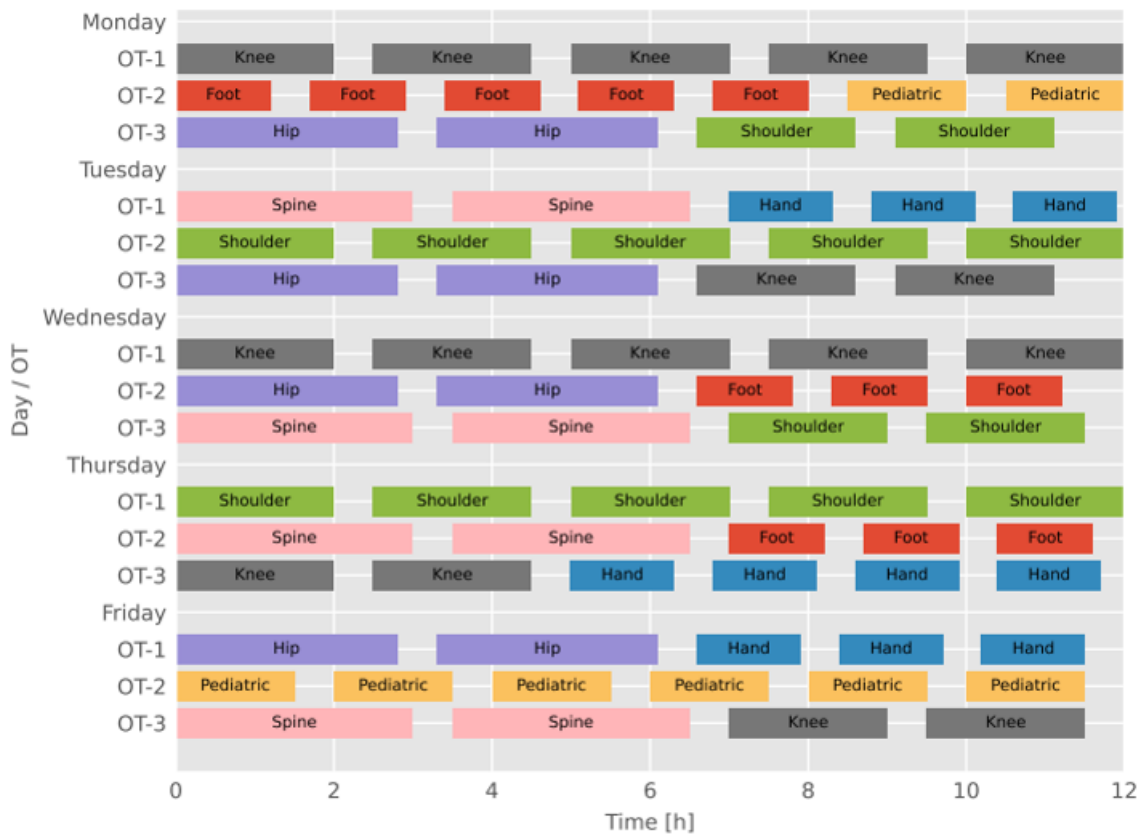


Figure A.15: Weekly MSS for experiment D1.

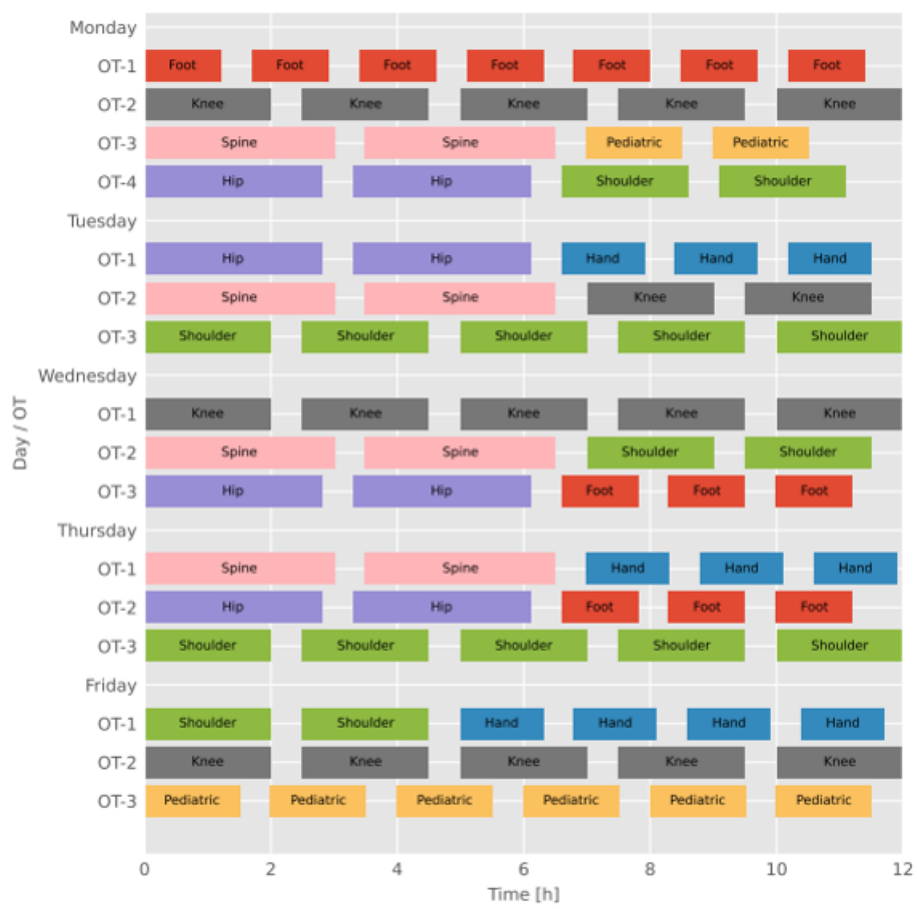


Figure A.16: Weekly MSS for experiment D2.

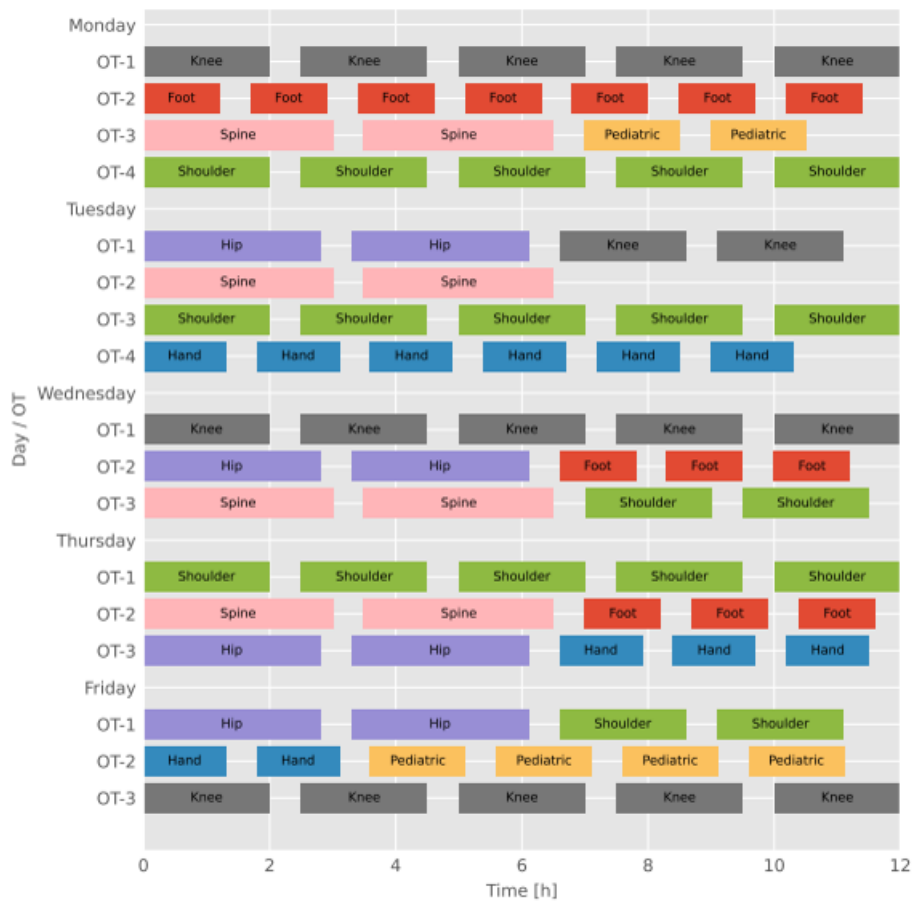


Figure A.17: Weekly MSS for experiment D3.

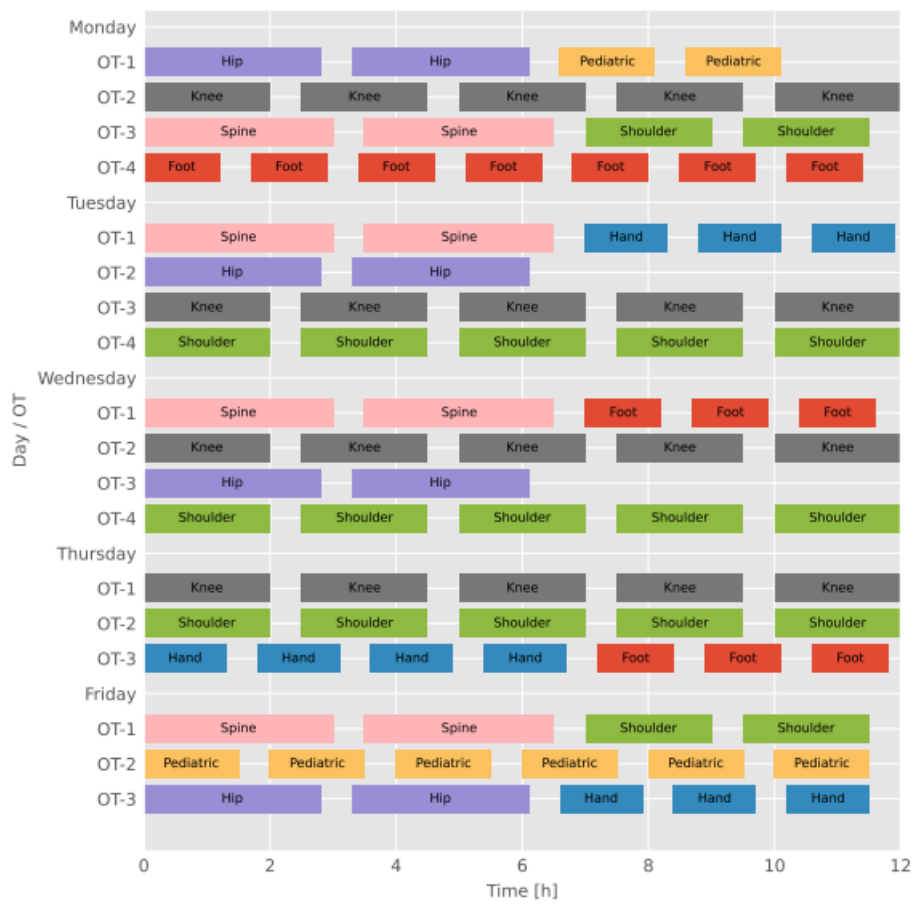


Figure A.18: Weekly MSS for experiment D4.

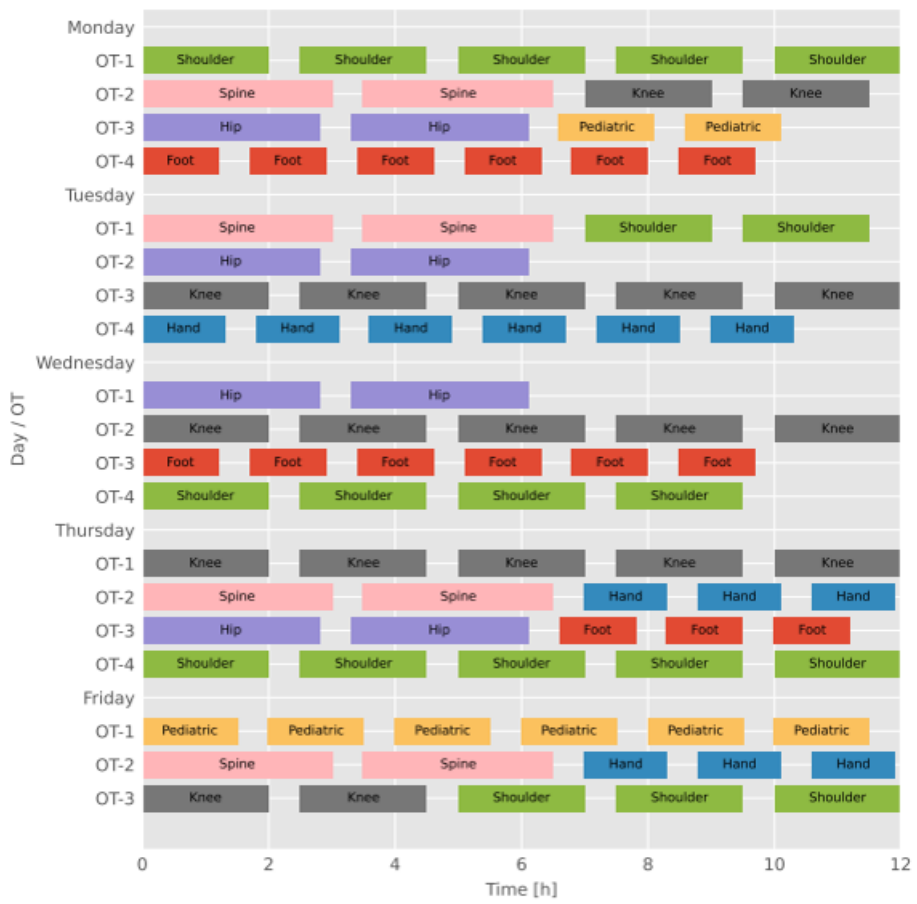


Figure A.19: Weekly MSS for experiment D5.

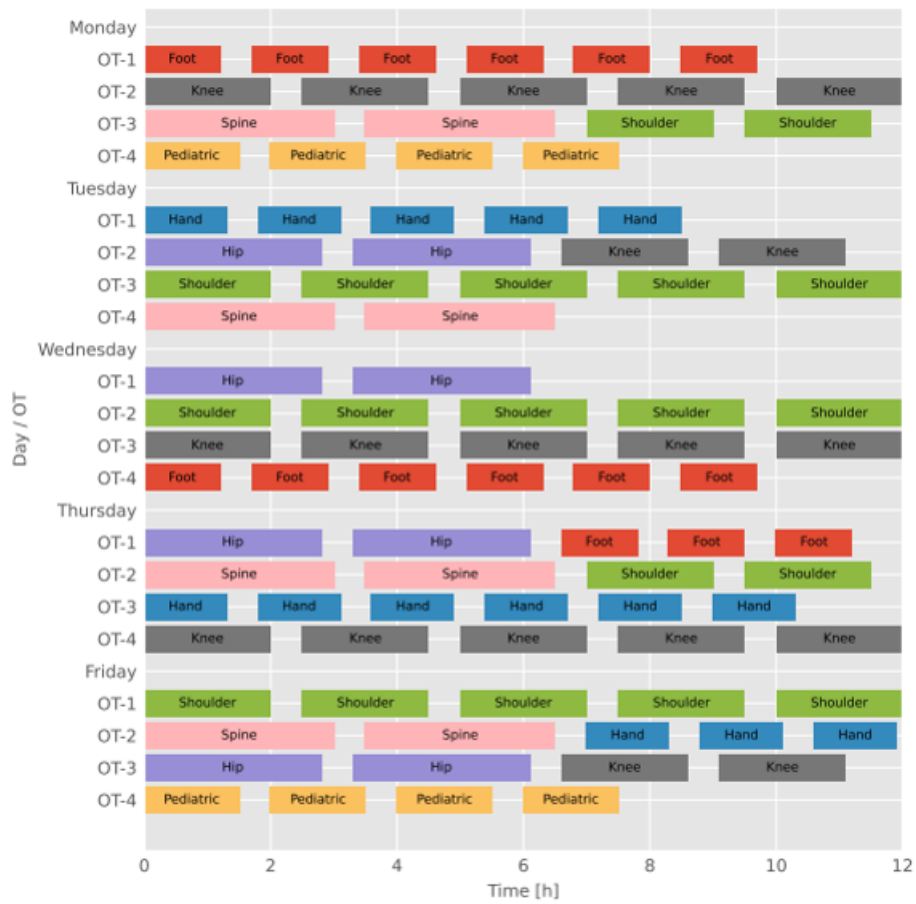


Figure A.20: Weekly MSS for experiment D6.

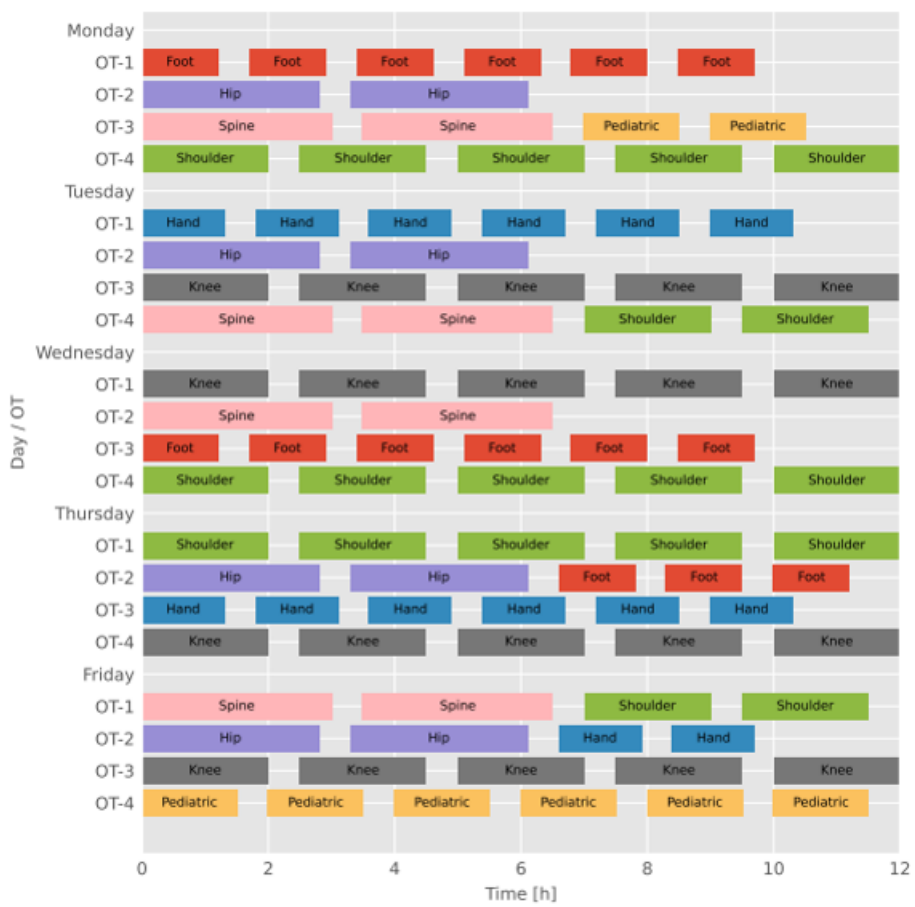


Figure A.21: Weekly MSS for experiment D7.

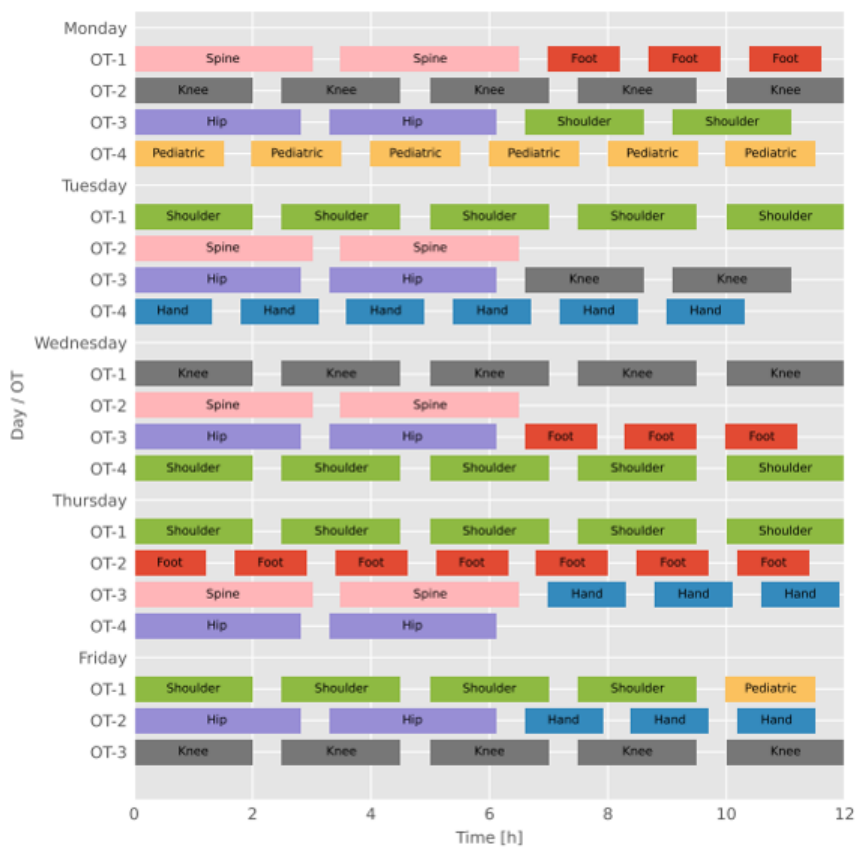


Figure A.22: Weekly MSS for experiment E1.

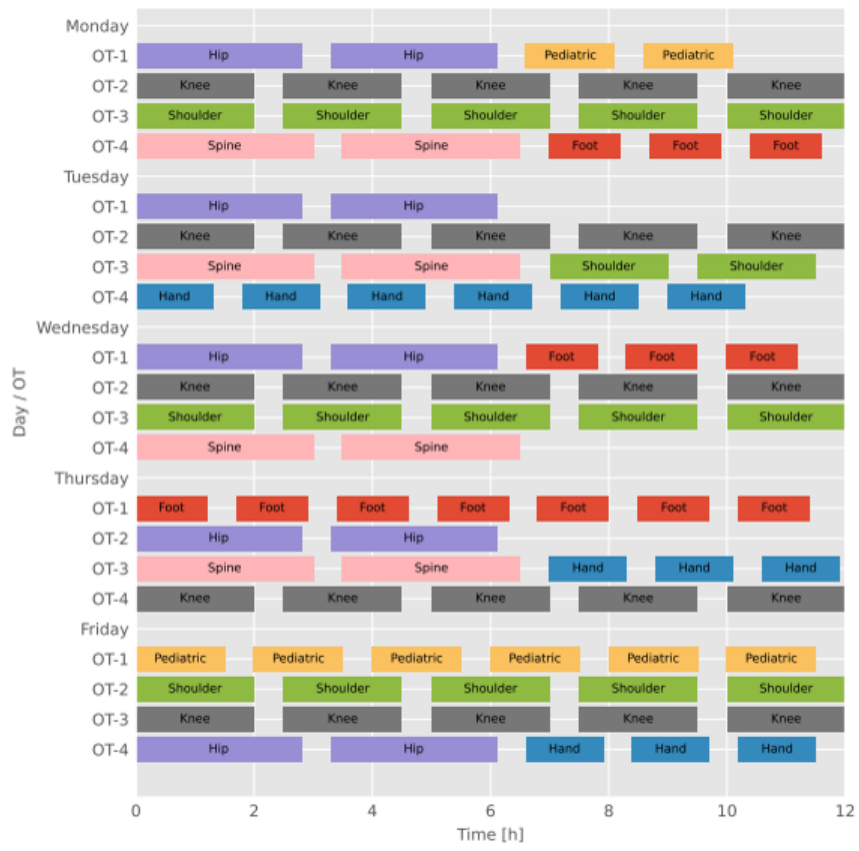


Figure A.23: Weekly MSS for experiment E2.

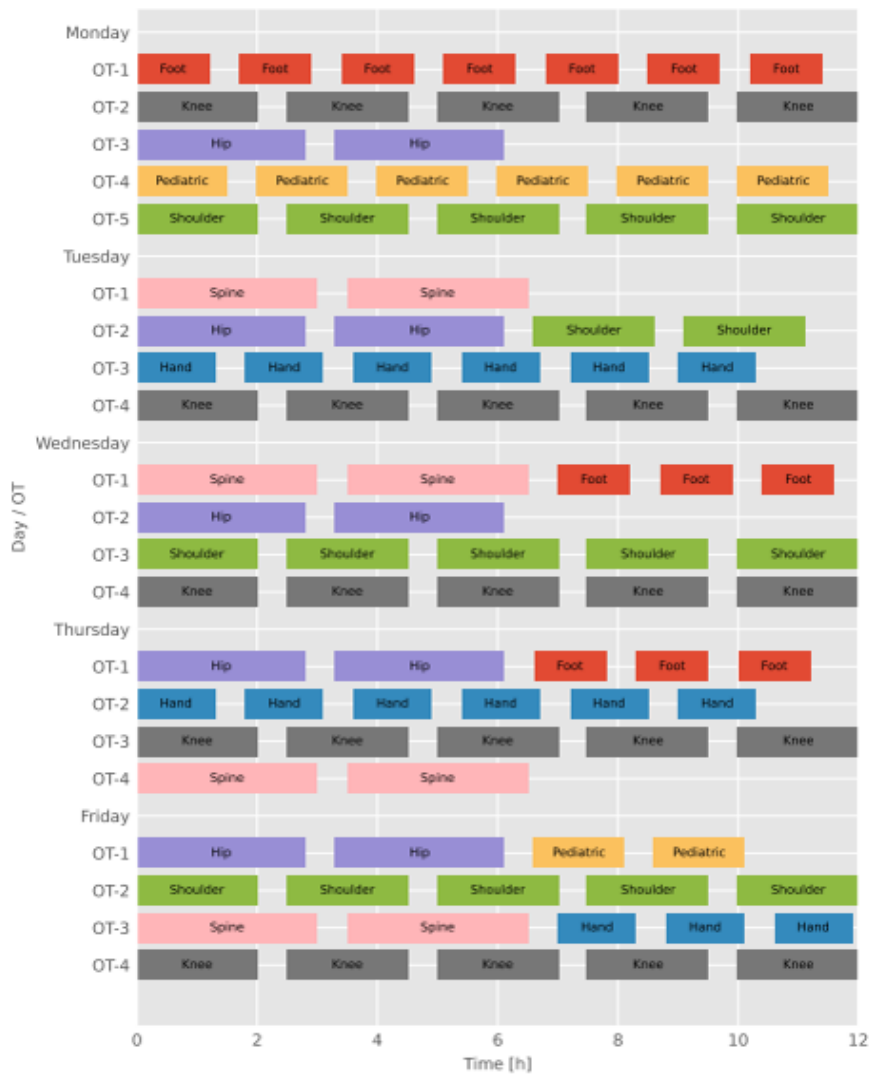


Figure A.24: Weekly MSS for experiment E3.

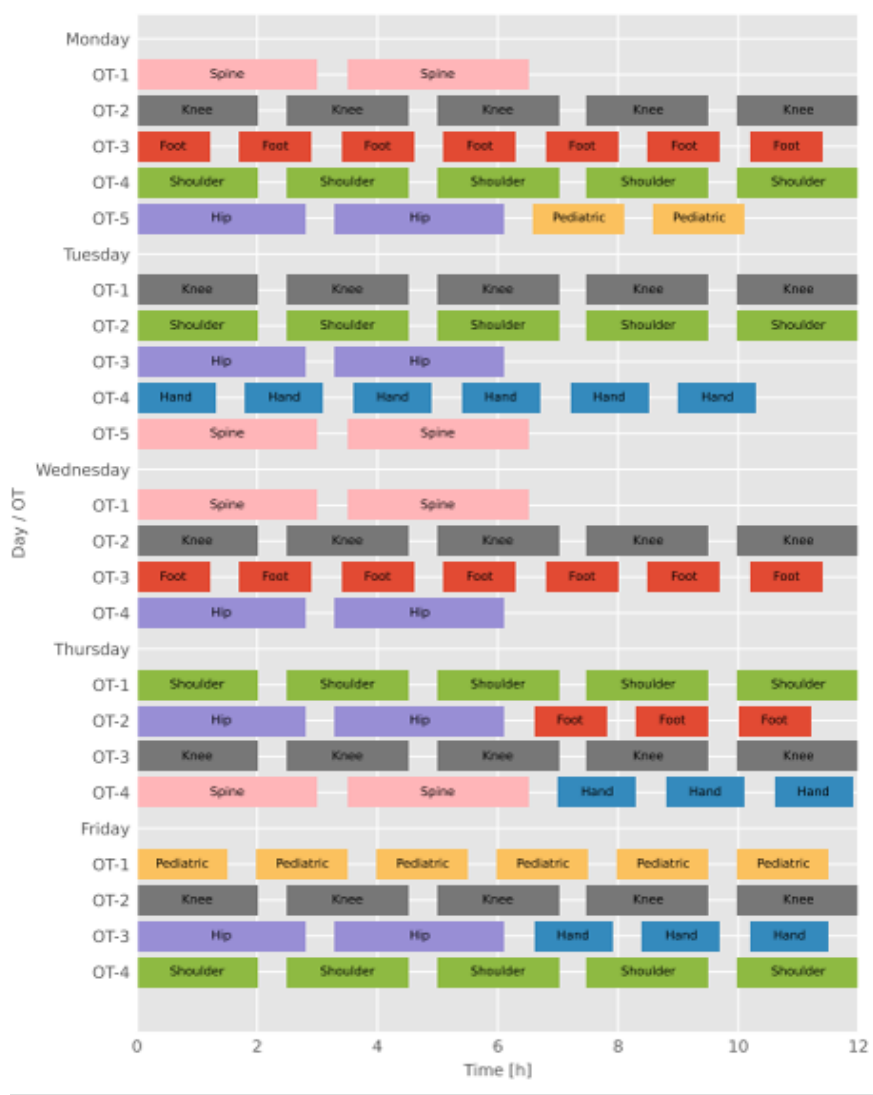


Figure A.25: Weekly MSS for experiment E4.

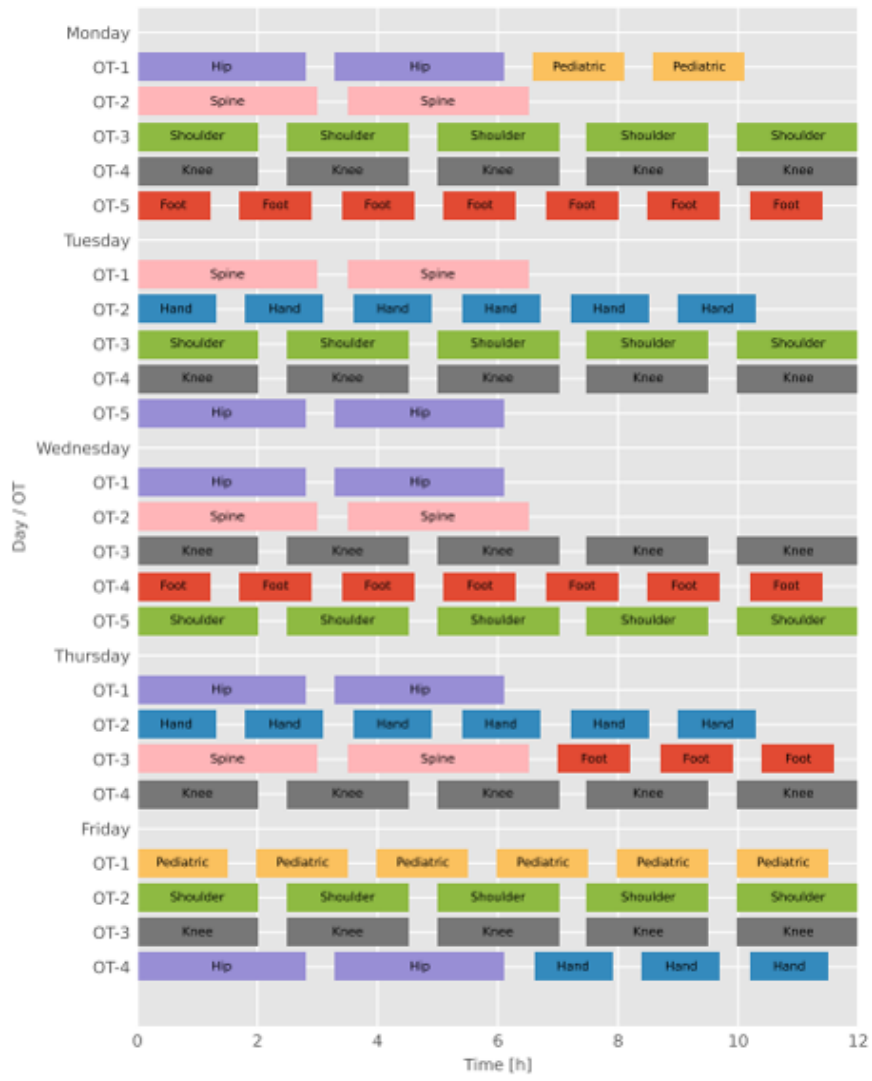


Figure A.26: Weekly MSS for experiment E5.

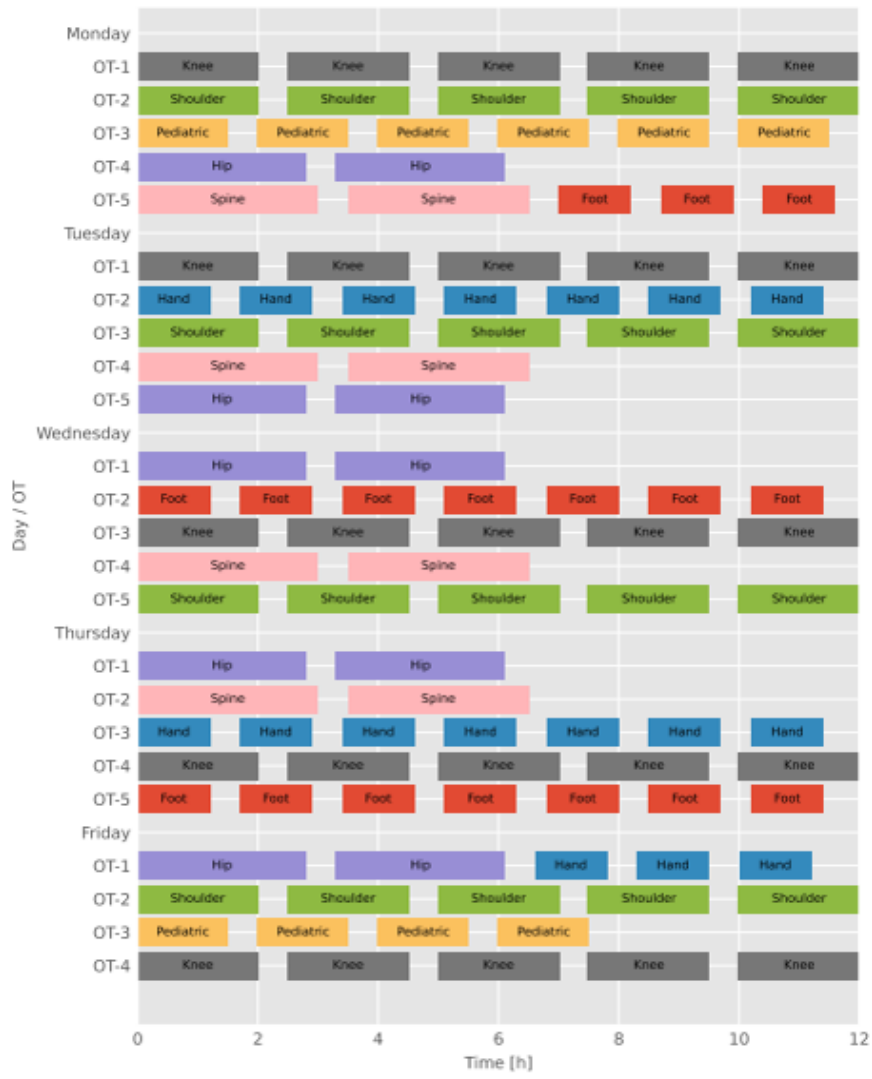


Figure A.27: Weekly MSS for experiment E6.

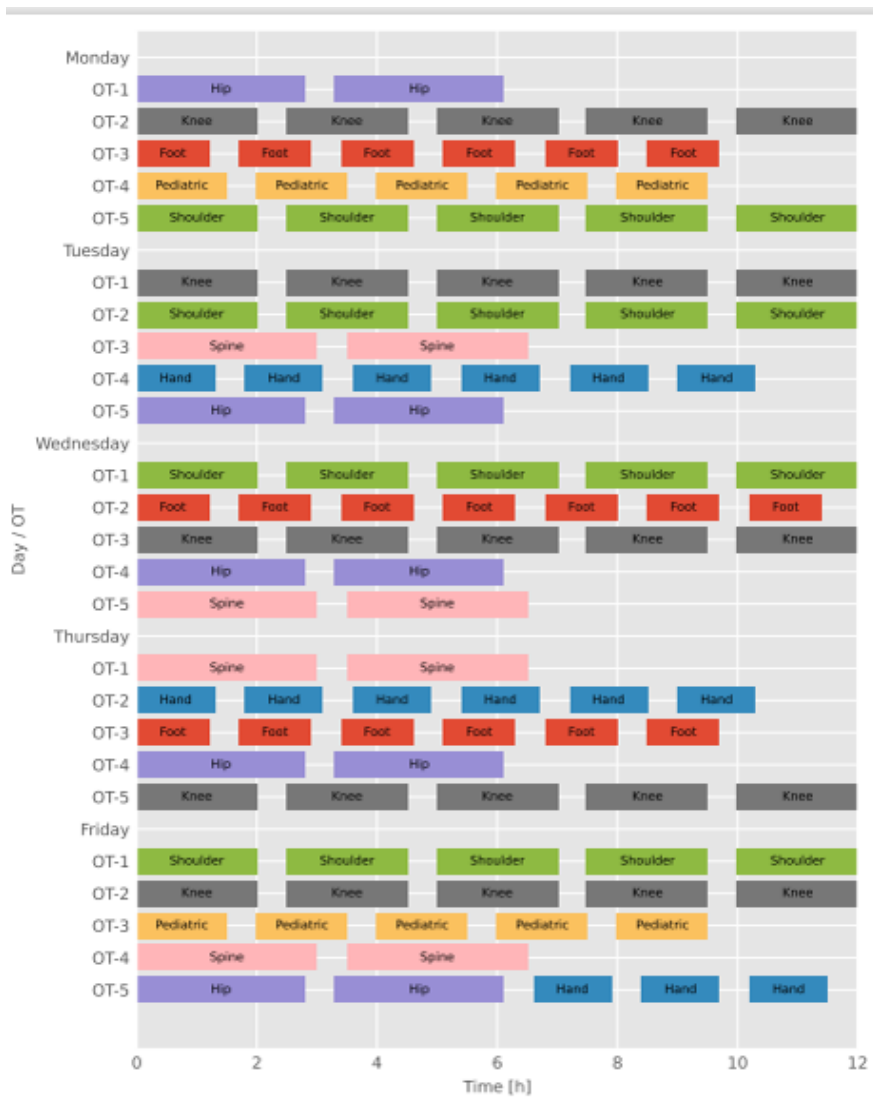


Figure A.28: Weekly MSS for experiment E7.

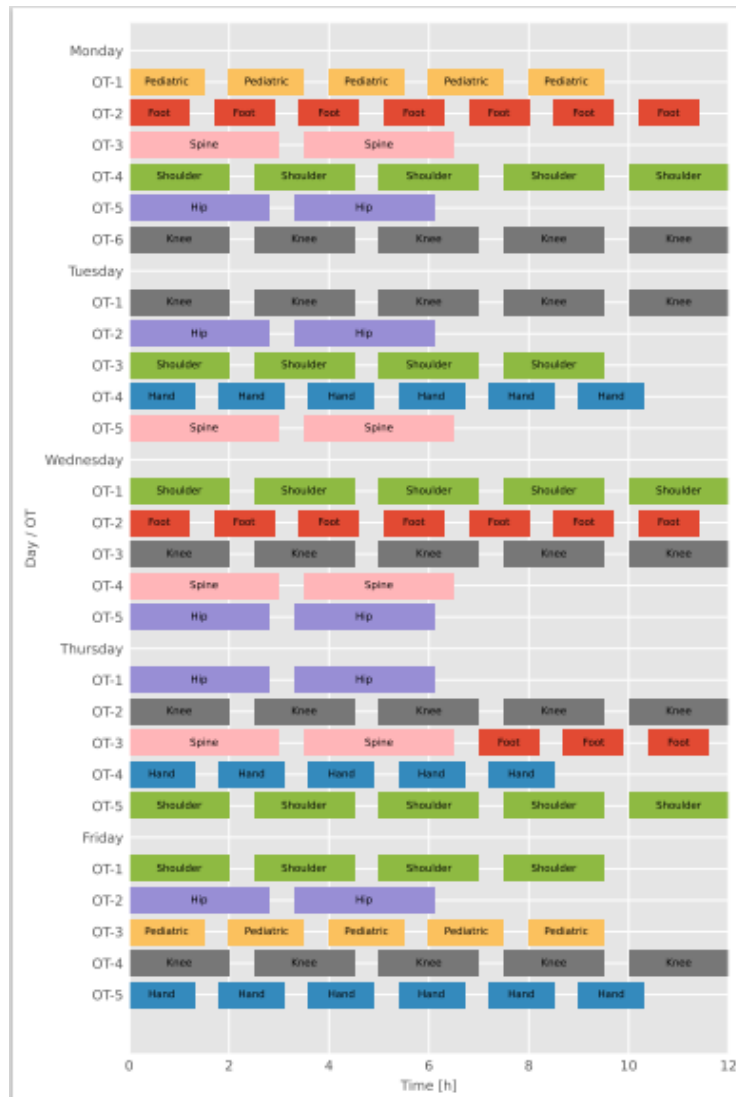


Figure A.29: Weekly MSS for experiment E8.



Figure A.30: Weekly MSS for experiment E9.



Figure A.31: Weekly MSS for experiment E10.

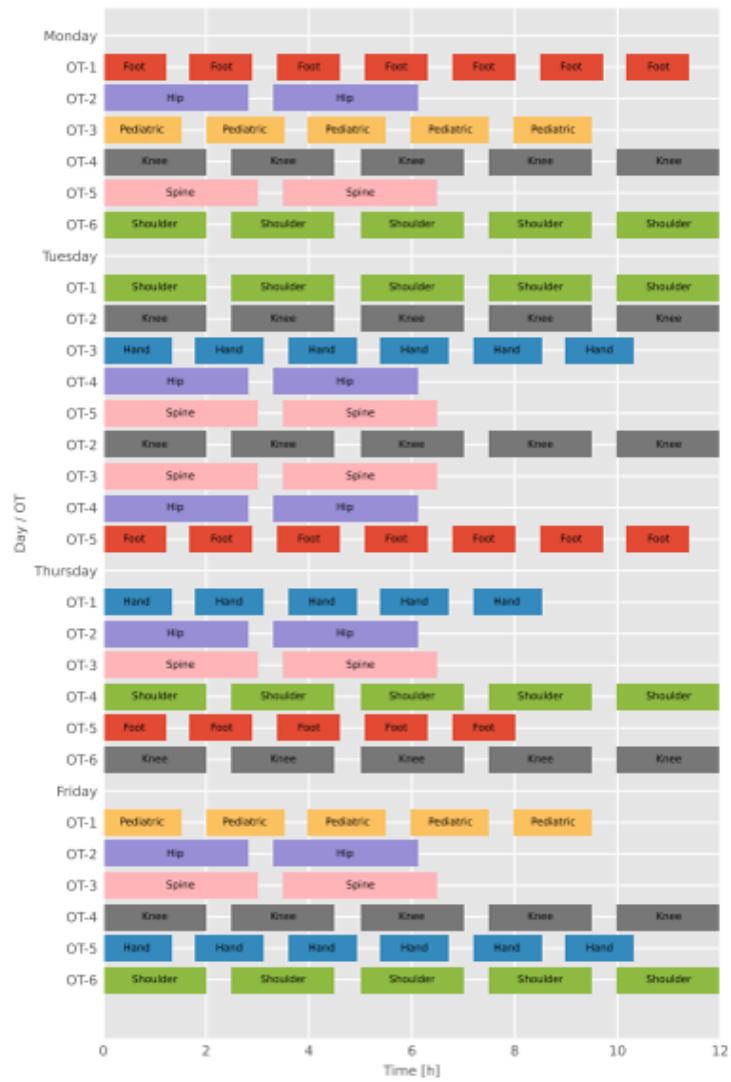


Figure A.32: Weekly MSS for experiment E11.

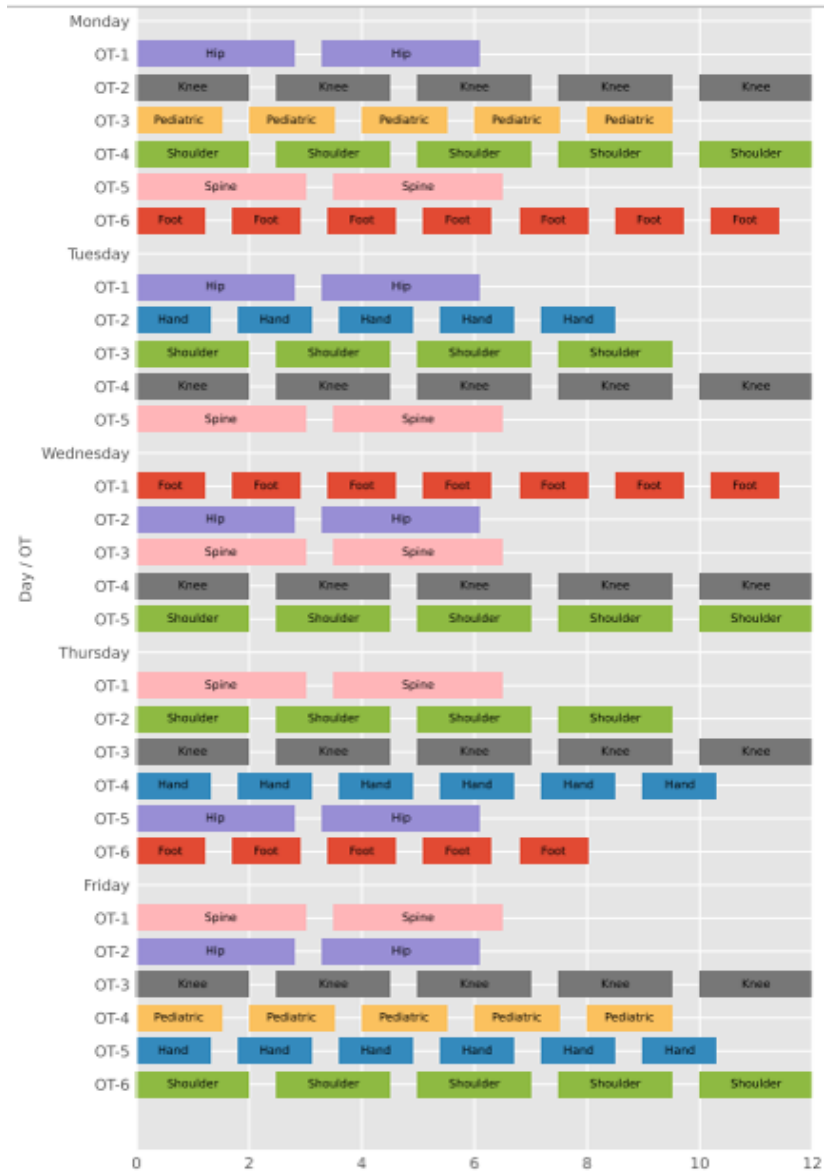


Figure A.33: Weekly MSS for experiment E12.

Appendix B

Post surgical bed allocation for experiments

Table B.1: Post surgical bed allocation for experiments A1-E12.

Experiment / Beds allocated	SICU								ICU								Ward							
	Hip	Spine	Knee	Shoulder	Hand	Foot	Pediatric	Total	Hip	Spine	Knee	Shoulder	Hand	Foot	Pediatric	Total	Hip	Spine	Knee	Shoulder	Hand	Foot	Pediatric	Total
A1	1	1	2	2	0	0	0	6	3	3	2	2	0	0	1	11	3	5	4	4	3	3	1	25
A2	1	1	2	1	0	0	1	6	3	3	3	3	0	0	0	12	3	5	4	4	3	3	1	24
A3	1	1	2	2	0	0	0	6	3	3	4	4	0	0	0	14	3	3	4	4	4	4	2	24
A4	1	1	1	2	0	0	5	3	3	4	4	0	0	0	0	14	3	3	4	4	4	4	2	24
A5	1	1	1	2	0	0	0	5	3	3	3	4	0	2	0	15	3	3	4	4	3	3	3	25
B1	1	1	2	1	1	0	0	6	3	3	3	4	1	0	0	14	5	3	4	4	2	4	3	25
B2	1	1	3	2	0	0	1	8	3	3	4	2	0	0	0	12	5	3	6	4	4	4	2	28
B3	1	1	3	2	0	0	1	8	3	3	4	2	0	0	0	12	5	3	6	4	4	4	2	28
B4	1	1	2	2	0	1	0	7	3	3	4	4	0	0	0	14	5	3	6	6	4	4	3	31
C1	1	1	2	2	0	0	2	8	4	3	3	4	0	0	0	14	5	3	8	4	3	5	4	32
C2	1	1	2	2	0	0	0	6	4	3	3	4	0	0	0	14	5	5	6	6	3	4	6	35
C3	1	1	2	3	0	0	0	7	4	4	3	4	0	0	0	15	5	5	6	6	3	4	6	35
C4	1	1	2	2	0	0	0	6	4	4	5	3	0	0	0	16	5	5	6	6	3	7	5	37
C5	1	1	2	2	0	0	0	6	4	4	3	4	0	0	1	16	5	5	6	6	6	7	4	39
D1	1	1	2	2	0	0	0	6	4	4	4	4	0	0	0	16	5	5	6	6	4	5	6	37
D2	1	1	2	2	0	0	0	6	4	4	3	5	0	0	0	16	5	5	6	6	4	7	6	39
D3	1	1	2	3	0	0	0	7	4	4	3	5	0	0	0	16	5	5	6	6	6	7	4	39
D4	1	1	2	2	0	0	0	6	4	4	4	4	0	0	0	16	5	5	8	8	4	7	6	43
D5	1	1	2	2	0	0	0	6	4	4	4	4	0	0	0	16	5	5	8	6	6	6	6	42
D6	1	1	2	2	0	0	0	6	4	4	4	4	0	0	0	16	5	5	8	8	6	6	4	42
D7	1	1	2	2	0	0	0	6	4	4	4	5	0	0	0	17	5	5	8	6	6	6	6	42
E1	1	1	2	2	0	0	0	6	5	4	3	4	0	0	0	16	5	5	6	8	6	8	6	44
E2	1	1	2	2	0	2	0	8	5	4	4	3	0	0	0	18	5	5	10	6	6	6	6	44
E3	1	1	2	2	0	1	0	7	5	4	4	3	0	0	0	16	5	5	10	6	6	6	6	44
E4	1	1	2	3	0	0	0	7	5	4	4	3	0	0	0	16	5	5	10	8	6	7	6	47
E5	1	1	2	3	0	0	1	8	5	4	4	3	0	0	0	16	5	5	10	8	6	7	5	46
E6	1	1	2	3	0	1	0	8	5	4	4	3	0	0	0	16	5	5	10	8	6	7	5	46
E7	1	1	2	3	0	0	0	7	5	4	4	3	0	0	0	16	5	5	10	8	6	7	5	46
E8	1	1	2	3	0	1	0	8	5	4	4	3	0	0	0	16	5	5	10	8	6	6	5	45
E9	1	1	2	3	0	0	0	7	5	4	4	3	0	0	0	16	5	5	10	8	6	7	5	46
E10	1	1	2	2	0	0	0	6	5	4	4	4	0	0	0	17	5	5	10	8	6	7	5	46
E11	1	1	2	3	0	0	0	7	5	5	4	3	0	0	0	17	5	5	10	8	6	7	5	46
E12	1	1	2	2	0	0	0	6	5	5	4	4	0	0	0	18	5	5	10	8	6	7	5	46